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Development of a spatial multicriteria approach to determine the location of loading/unloading spaces in urban centers

Desenvolvimento de uma abordagem espacial multicritério para determinar a localização de espaços de carregamento/descarregamento em centros urbanos

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ABSTRACT

This paper proposes an innovative solution approach that combines mathematical programming, multicriteria decision analysis, and a geographic information system (GIS) to determine the optimal number of loading/unloading spaces in urban centers. The proposed methodology was implemented in a case study in the urban center of Fortaleza, a municipality in the Northeast region of Brazil. Employing the hybrid method for selecting optimal loading/unloading spaces resulted in a 10% increase in the percentage of served clients compared to using solely the mathematical model. On the contrary, as the registered spaces were not determined using a scientific approach, clients located outside the Centro neighborhood experienced notably low service levels, with walking distances exceeding 450 meters.

RESUMO

Este artigo apresenta uma nova abordagem que combina programação matemática, métodos de multicritério de apoio à decisão e sistemas de informações geográficas para determinação do número ótimo de vagas para carga/descarga em centros urbanos. A metodologia proposta foi aplicada em um estudo de caso na cidade de Fortaleza, na região Nordeste do Brasil. O uso do método híbrido para a seleção das melhores vagas aumentou o percentual de cobertura dos clientes em 10%, em comparação com aplicação exclusiva de um modelo de programação matemática. Por outro lado, uma vez que a determinação dos potenciais candidatos a vagas não foi baseada em uma abordagem científica, clientes localizados fora da região central apresentaram baixos níveis de serviço, com distâncias de caminhada superiores a 450 m.

1. INTRODUCTION

Freight transportation is a complex area of study in city logistics since it contemplates the transportation of goods and the spaces available in the streets to deliver these goods. The efficiency and cost of urban freight distribution depend on the intelligent use of on-road loading and unloading spaces (Taniguchi and Tamagawa, 2005). Urban freight is of fundamental importance in the modern economy since the majority of the world's population is living in great urban centers. Furthermore, with the massification of e-commerce, the number of deliveries is increasing over the years.

Increases in the frequency distribution of orders for retailers exacerbate problems with freight vehicle parking in urban centers. Urban centers usually present a very dense road infrastructure and several accessibility restrictions, making the parking operations of freight vehicles more difficult (Crainic, Ricciardi and Storchi, 2004). The location of loading and unloading spaces for urban freight delivery is a key issue in traffic management and the fulfillment of delivery deadlines (Neghabadi, Evrard Samuel and Espinouse, 2019).

Furthermore, even when the city plans for the provision and management of loading-unloading spaces, in some cases, passenger vehicles often occupy the spaces designated for freight vehicles. In Tokyo and Belo Horizonte cities, passenger cars use 54% and 56% of the parking spaces, while freight vehicles use only 22% and 37.5%, respectively (Aiura and Taniguchi, 2005). In order to minimize the influence of the loading-unloading operations on traffic, the Brazilian traffic legislation states that these operations should be carried out on the road, and that the vehicles should be positioned in the "low direction, parallel to the roadway and along the pavement, on the stops or parking places, with properly marked exceptions".

Though these spaces are predetermined by traffic agencies, transport operators in central areas find it difficult to locate designated parking spaces for loading-unloading operations due to the density of retailers (Oliveira, 2014). Latin American cities mirror this trend, with scant regulated parking spaces destined for freight transport. Buenos Aires had a mere 750 regulated spaces in 2009 (Dablanc, 2009), while central Belo Horizonte tallied only 550 such areas in 2014 (Oliveira, 2014). Researchers, in response, have harnessed quantitative methodologies, decision support systems, simulation models, and Geographic Information Systems (GIS) to optimize the allocation of loading-unloading spaces, aiming to elevate service standards (Neghabadi, Evrard Samuel and Espinouse, 2019).

Several multicriteria decision analysis methods have been developed in the last few decades. In this paper, we selected the MACBETH method, considering its main advantages (Bana e Costa, de Corte and Vansnick, 2012):

a) It is user-friendly and accessible to decision-makers without specialized technical knowledge;
b) It is flexible and adjustable to distinct decision-making contexts;
c) It is a consistent approach for comparing and evaluating alternatives.

Regarding the Analytical Hierarchy Process (AHP), a well-known decision-making technique used in the same context as MACBETH, we can emphasize the following main differences (Bana e Costa and Vansnick, 1999; Mardle, Pascoe and Herrero, 2004; Ishizaka and Nemery, 2013).

a) AHP decomposes complex decision problems into a hierarchy of criteria and alternatives, utilizing pairwise comparisons to establish priority scales and weights. In contrast, MACBETH employs qualitative judgments through bipolar qualitative assessments (semantic scales) to evaluate criteria and alternatives;

b) AHP uses numeric ratios for pairwise comparisons (e.g., 1 to 9 scale) to quantify the intensity of preference. In contrast, MACBETH employs qualitative scales with predefined descriptors (e.g., 'slightly preferable,' 'strongly preferable,' etc.) to assess preference;

c) While AHP typically assumes that decision-makers can offer precise judgments in pairwise comparisons, which may not fully capture uncertainty or imprecision, MACBETH enables decision-makers to express preferences using qualitative terms. This approach better accommodates uncertainty and subjective judgment.

This paper aims at presenting a spatial multicriteria approach to determine the localization of loading and unloading spaces in urban centers. Our proposal combines a MILP model, a MACBETH multicriteria decision modeling, and spatial analysis in selecting the optimal number and location of such facilities so as to increase the percentage of covered retailers and minimize the walking distance of loading-unloading operations.

The main innovations of this work are described below.

- The MILP model is a set covering-based formulation that determines the best location for the parking spots considering the maximum walking distance. Furthermore, this formulation still provides the minimum number of facilities to cover all the clients under consideration;
- A multicriteria decision method is used combined with a MILP formulation to select the best places for loading/unloading spaces, considering multiple criteria. This hybrid approach leads to solutions that satisfy real-world requirements;
- A spatial analysis is applied conjointly with the Operational Research techniques. Indicators such as the Kernel Density Estimator and the Moran Index are calculated to provide additional information to support the decision process.

In the best knowledge of the authors, there are no other contributions providing a solution approach that embraces the combinatorial nature of the problem, distinct criteria from the decision makers, and spatial analysis. As outlined in the literature review, previous studies have independently applied simulation, optimization, and spatial analysis to address related issues.

The remainder of this paper is structured as follows: Section 2 presents the literature review of related problems. Section 3 introduces the proposed decision support system. Section 4 outlines the case study. Section 5 provides a discussion of the results. Finally, Section 6 offers the conclusions and suggests potential future research directions.

2. LITERATURE REVIEW

An aspect of urban freight distribution is the rational use of loading and unloading spaces in urban areas for goods distribution, considering a lack of an intelligent allocation of parking spaces can lead to a high occupancy rate for other types of vehicles (Oliveira, 2014). The allocation of parking spaces for loading and unloading operations has been explored in the literature using optimization and simulation models to determine the optimal number and location of parking spaces, with the goal of maximizing service level, such as the percentage of covered retailers, time period for loading/unloading operations, traffic and delivery costs. Table 1 summarizes several approaches proposed in the literature.

We consider three criteria in the proposed methodology, as detailed in Section 3: distance of each loading/unloading space to the nearest major road, density of clients within a 100-meter radius, and client's frontal distance. In this context, we discuss how these criteria have been addressed in the current literature.

Aiura and Taniguchi (2005) considered the behavior of pickup-delivery vehicles, implicitly involving the distance to major roads for optimizing on-street loading/unloading spaces. However, the other two criteria are not specifically mentioned. Roca-Riu, Fernández and Estrada (2015) focused on parking slot assignments and likely considered proximity to major roads for accessibility, although this criterion is not explicitly stated. Nevertheless, the remaining criteria are not specifically mentioned. Chen and Lin (2017) addressed a fuzzy collaboration system for loading/unloading space recommendations, potentially considering proximity to the clients. However, distance to major roads and density of clients are not explicitly considered. Roca-Riu et al. (2017) designed dynamic delivery parking spots, which included considerations for proximity to major roads to reduce traffic disruptions. However, the density of clients and the client's frontal distance are not directly specified. Alho et al. (2018) optimized the location and usage of loading/unloading bays, which included considerations for proximity to major roads. Although the remaining criteria were not explicitly addressed.

Imane and Fouad (2019) developed a methodology for planning loading/unloading spaces that considers real-world scenarios, likely including the distance to major roads. Nonetheless, the other criteria are not specifically mentioned. Santos Junior and Oliveira (2020) included in their proposal the level of service of unloading zones, which implicitly involves the distance to major roads. However, the client's frontal distance and the density of clients are not explicitly addressed. Shahparvari et al (2020) proposed a GIS-LP integrated approach for logistics hub location that considers spatial analysis, including distance to major roads. Yet, the other considered criteria are not specifically mentioned. Cruz-Daraviña and Suescún (2021) studied freight operations in city centers, likely including considerations for proximity to major roads. However, the density of clients and the client's frontal distance are not directly specified. Silva et al. (2024) focused on improving freight parking needs and considered city logistics initiatives that likely include proximity to major roads. Nevertheless, the remaining criteria are not specifically mentioned.

Concerning the distance to major roads, most studies implicitly consider this factor in their analysis, although it is not always explicitly mentioned. Regarding the density of clients, none of the articles mentioned evaluating client density within a 100-meter radius. Finally, regarding the client's frontal distance, only one article explicitly addressed this criterion. This analysis indicates that while proximity to major roads is commonly considered, explicit mentions of client density and frontal distance are less frequent in the existing literature. In this context, the proposed methodology represents an advancement compared to the reviewed literature.

Based on the analysis of the previous work, we can observe that the lack of parking spaces in urban centers affects the traffic system, increasing the travel times for the users and the loading and unloading times for the logistic operators. Still considering the state-of-the-art, faced with distinct interests from different stakeholders, multi-criteria decision approaches can provide richer solutions to be implemented in real-world scenarios.

Table 1: Approaches from literature.

Reference	Solution approach	Main results
Aiura and Taniguchi (2005)	Traffic simulation	Determination of the optimal location of on-street loading/unloading spaces for the minimization of the total delivery cost.
Roca-Riu, Fernández and Estrada (2015)	MILP formulations	Definition of loading/unloading spaces considered the time period in which the parking spaces were occupied by the carrier.
Chen and Lin (2017)	Quadratic programming and fuzzy logic	Location of loading/unloading spaces to support the smooth operations of a logistics company.
Roca-Riu et al. (2017)	Simulation	Dynamic location of loading/unloading spaces in urban freight distribution systems.
Roca-Riu, Fernández and Estrada (2015)	GIS and spatial analysis methods	Monitoration loading/unloading spaces used by delivery vehicles in European cities, as well as to infer the paths taken by these vehicles.
Alho et al. (2018)	Microsimulation	Optimization of the configuration of loading/unloading spaces in urban centers.
Imane and Fouad (2019)	Theoretical and empirical approach	Location of loading/unloading areas in commercial streets. A case study at Casablanca (Morocco) is presented.
Santos Júnior and Oliveira (2020)	Multiplex network	Analysis of the accessibility to the loading/unloading spaces and the service level. A case study at Belo Horizonte (Brazil) is presented.
Shahparvari et al. (2020)	Multicriteria decision approach coupled with GIS	Localization of potential zones for a consolidation center in Iran.
Cruz-Daraviña and Suescún (2021)	Multicriteria decision approach	Analysis of loading and unloading operations in Cali's city-center, so as to understand the land use conflict between freight operations and public space planning.
Silva et al. (2024)	Freight trip generation model	Determination of loading and unloading spaces based on the freight parking demand. Case studies in São João Del Rei and Itajubá (Brazil) are presented.

3. PROPOSED DECISION SUPPORT TOOL

3.1. An overview of the proposed methodology

In this section, we describe the proposed approach to determine loading/unloading spaces for urban freight distribution. Our methodology comprises five steps. First, spatial data regarding registered loading/unloading spaces, clients, and the road network were compiled into a geographic database. Then, we determined the optimal number and location of loading/unloading spaces using a MILP model. The distances between clients and spaces implemented in the model were derived from the least-cost algorithm and spatial data. Thirdly, for the MACBETH multicriteria decision approach, we calculated a weighted average considering three criteria determined from the literature and the results of a questionnaire. Then, based on the number of spaces determined from the MILP model, we ordered the spaces in decreasing order and selected those with the highest weighted average values. The objective was to compare the performance of the MILP model with a combined model resulting from the integration of the MILP model with the MACBETH multicriteria decision approach. Fourthly, we analyzed the percentage of covered and uncovered clients and examined various scenarios of walking distance from each loading and unloading space. Finally, to identify potential zones or clusters with higher and lower service levels in our case study, we conducted an autocorrelation analysis using the Local Moran Index. Figure 1 illustrates the main steps of the proposed methodology, which are described in sections 3.2 to 3.6.

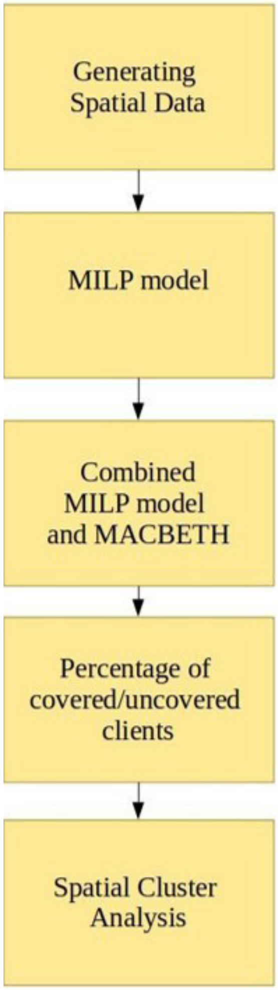

Figure 1. Main steps used to select the optimal number and location of loading/unloading spaces in urban centers.

3.2. Generating spatial data

To determine the optimal number and location of loading/unloading spaces, we organized spatial datasets comprising loading/unloading spaces, clients, the road network, and urban blocks. These datasets served as inputs to derive each criterion adopted in both the MILP model and the combined MILP and MACBETH approach.

In the MILP model, only the distances along the road network between each loading/unloading space and client were considered to determine the optimal number and location of loading/unloading spaces.

For the combined approach, the optimal number of locations was predetermined by the results from the MILP model, while their specific locations were determined by the MACBETH multicriteria decision approach. The criteria considered in the MACBETH approach were as follows:

1. The distance of each loading/unloading space to the nearest major road;
2. The density of clients within a 100-meter radius;
3. The client's frontal distance.

These criteria were defined based on the study by Dablanc (2009), which stipulates that in Paris, on-street parking spaces must be at least 10 meters long, and there must be at least one delivery per 100 meters along city streets. Additionally, insights from a questionnaire were incorporated through consultation with peers.

3.2.1. Distance of spaces to clients and major roads

To determine the distances between loading/unloading spaces and clients, as well as to major roads, we utilized the least-cost algorithm within a GIS environment, employing spatial data of the road network and urban blocks. This algorithm, commonly known as the Dijkstra algorithm (Dijkstra, 1959), aims to find the lowest-cost path by analyzing neighboring nodes (origin and destination points) and selecting the path with the lowest accumulated cost, while ensuring that nodes already visited are discarded. In order to do that, a cost image has to be generated and used as input to the algorithm.

In QGIS v3.10, a cost image was generated using spatial data of the road network and urban blocks. High cost values were attributed to urban blocks, while low cost values were assigned to the road network, effectively guiding paths through the road network.

Using this algorithm, multiple paths were generated from clients to loading/unloading spaces, ensuring they passed through the road network. The distance of each path was then calculated and incorporated into a distance matrix, which served as input for the MILP model. It's essential to note that the MILP model considers as input to the model only the distance between each client and loading/unloading space.

Additionally, the least-cost algorithm was also employed to determine the distance from each loading/unloading space to major roads, being a criterion used in the combined MILP and MACBETH approach. In this case, the destination points were located on the major roads, which were extracted from the road network spatial data.

3.2.2. Density of clients

To determine the concentration of clients in our study area, we used the planar kernel density algorithm. The Planar Kernel Density Estimator (KDE) depends on two parameters for its calculation: the radius of influence *r* and the kernel density function *k* (Equation 5). The calculation of the kernel density was based on the quartic kernel function *k* (Equation 1). The radius of influence was a radius of 100m from the client's location.

$$\lambda(s)=\sum_{i=1}^{N}\frac{1}{\pi^2}\times k\times\left(\frac{d_{is}}{r}\right) \tag{1}$$

Where:

(s) = location density at s;

r = search radius (bandwidth)

k = weight of a point i at a distance d_{is}

k is a modeled function between the d_{is} and the r

3.2.3. Frontal distance

The frontal distance of each client was estimated using the ruler tool available in Google Earth, using satellite images provided by the platform. Subsequently, this information was integrated into the client's attribute table. Through a proximity analysis conducted using QGIS v3.10, we were able to determine the nearest loading/unloading space for each client.

By associating the information from the client's attribute table with the loading/unloading spaces data, we could ascertain the available parking space in front of each client. This criterion provided insights into the parking space availability directly in front of each client's location.

3.3. A MILP model to determine the number of loading/unloading spaces

There is a trade-off between the number of loading/unloading spaces and the walking distance of the deliveries. We present a MILP model to determine the optimal number of loading/unloading spaces, given a maximal walking distance *R*. We consider that a client *i* can be covered by a loading/unloading space *j* if the distance $d_{ij} \leq R$. We extended the relaxed unicost set-covering problem proposed by Prata, Oliveira and Holanda (2018). Hereafter, we present the notation used in the proposed MILP formulation.

Indices and sets

i: index for clients {1, 2,…,*m*}.

j: index for loading/unloading spaces {1,2,…,*s*}.

Parameters

a_{ij} = 1, if client *i* can be covered by loading/unloading space *j*; 0, otherwise.

P: penalty factor (a sufficiently large integer number).

Decision variables

y_j = 1, if loading/unloading space *j* is selected; 0, otherwise.

u_i = 1, if client *i* is not covered by any loading/unloading space; 0, otherwise.

$$Minimize\, z = \sum_{j=1}^{s} y_j + P \sum_{i=1}^{m} u_i \tag{2}$$

subject to:

$$\sum_{j=1}^{s} a_{ij}\, y_j + u_i \geq 1; \forall_i \tag{3}$$

$$y_j \in \{0,1\}; \forall_j \tag{4}$$

$$u_i \geq 0; \forall_i \tag{5}$$

The objective function (Equation 2) minimizes the number of loading/unloading spaces and the number of uncovered clients. If the client i is not covered, constraint set (Equation 3) implies that z_i equals one. Constraint sets (Equation 4) and (Equation 5) determine the domain of the decision variables. Given the constraint set (Equation 3), the integrality of the decision variables u_i can be relaxed.

3.4. A combined MILP and MACBETH approach

In our combined approach, we utilized two distinct methodologies: the MILP model to define the number of loading/unloading spaces and the MACBETH multicriteria decision approach to determine their locations. The MACBETH method, short for Measuring Attractiveness by a Category Based Evaluation Technique, stands out among other multicriteria methods due to its reliance on qualitative judgments (Bana e Costa, Angulo-Meza and Oliveira, 2013; Bana e Costa *et al.*, 2010). This involves individuals or groups assessing the relative attractiveness of options through paired comparisons. Following these judgments, the MACBETH software automatically scrutinizes the consistency of choices, offering suggestions to rectify any inconsistencies (Bana e Costa *et al.*, 2010).

To facilitate qualitative judgments, we developed an online questionnaire using Google Forms, which is available at the Supplementary Material, accessible over a 30-day period. Participants were prompted to classify the three criteria and to assess the attractiveness of one criterion relative to another, with options ranging from equal relevance (N0) to extremely relevant (N6). Utilizing MACBETH 2 software, we inserted the predominant responses regarding the level of relevance of each criterion in order to generate a qualitative judgment matrix. This matrix served as the foundation for establishing an interval scale, with values ranging from 0 to 1. We adhered to the approach elucidated by Bana e Costa, de Corte and Vansnick (2012) for transforming qualitative judgments into a quantitative scale. These numeric values were then utilized as weights in the subsequent weighted average analysis. Then, within QGIS v3.10 software, we computed a weighted average image, considering the normalized spatial data of each criterion according to Equation 6, which was applied prior to calculating the weighted average, as outlined in Equation 7.

$$Cr_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{6}$$

Cr_i = the normalized criterion;
X_i = the pixel value;
X_{min} = the minimum value;
X_{max} = the maximum value.

$$\underline{x} = \frac{\sum_{i=1}^{N} w_i \times Cr_i}{\sum_{i=1}^{N} w_i} \tag{7}$$

Where:
$\underline{x}$: weighted average;
w_i : weights, obtained from MACBETH;
Cr_i : normalized criterion.

The process involved extracting weighted average values for each loading/unloading space from the weighted average image, which were later arranged in descending order. Then, guided by the number of loading/unloading spaces determined by the MILP model, we selected those spaces with the highest values.

3.5. Calculation of the percentage of covered/uncovered clients

The loading/unloading spaces chosen from both the MILP model and the combined approach served as the basis for estimating the percentage of clients covered and uncovered across various walking distance scenarios. To achieve this, buffers were created in QGIS v3.10, with radii corresponding to different walking distances, around each loading/unloading space. The number of clients within each buffer was then tallied to ascertain the percentage of covered clients. Conversely, clients located outside these buffers were considered uncovered, as they were not within the vicinity of the loading/unloading spaces.

3.6. Spatial cluster analysis

The density of covered and uncovered clients was computed for every road segment across various walking distance scenarios, utilizing the road network dataset. This dataset was then subjected to spatial autocorrelation analysis to assess the efficacy of both the MILP model and the combined approach in determining the optimal number and placement of loading/unloading spaces. The analysis employed the local Moran's index, conducted using the GeoDa software, available for free download at GeoDa (2024).

3.6.1. Moran index

The Moran's index provides insights into the degree to which the density of clients, whether covered or uncovered by the selected spaces within a road segment, correlates with those of its immediate neighbors. Given our focus on local relationships, we chose to employ the local Moran Index, a component of the Local Indicators of Spatial Analysis (LISA) indices.

In the context of spatial autocorrelation, the analysis hinges on neighborhood delineation. Therefore, the initial step involves establishing a spatial proximity matrix. This matrix assigns weights ranging from 0 to 1 to each element based on its shared borders with neighboring areas (Anselin, 1995). In our analysis, we utilized the "queen" neighborhood criterion, considering four immediate neighbors to compute the spatial proximity matrix.

Subsequently, utilizing the values derived from the proximity matrix, the Moran's Index was computed in accordance with Equation 8. Here, the attribute value (z) represents the average density of clients, whether covered or uncovered by the selected loading/unloading spaces, within each area, defined by road segments (Anselin, 1995).

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(z_i - \underline{z}\right)\left(z_j - \underline{z}\right)}{\sum_{i=1}^{n} \left(z_i - \underline{z}\right)^2} \tag{8}$$

Where:
I = Moran's index;
n : the number of areas;
z_i : the value of the attribute for area .^{i}.;
$\underline{z}$: the mean value of the attribute in the study region;
w_{ij} : weights of the normalized spatial proximity matrix.

The Moran index underwent a rigorous examination, with the null hypothesis positing spatial independence. To test this hypothesis, we employed the pseudo-significance test as outlined by Anselin (2005). This method involved generating various permutations of attribute values for each region. Each permutation resulted in a new spatial configuration, with attribute values redistributed across the areas. Among these permutations, only one mirrored the observed scenario, allowing us to construct an empirical distribution of the Moran index (I).

To determine statistical significance, we compared the originally measured index value to the extremes of the simulated distribution. If the measured value fell within an “extreme” range of the simulated distribution, it indicated statistical significance (Anselin, 1995, 2005). This rigorous testing approach ensured robust evaluation of spatial relationships and their significance within the analyzed data.

4. CASE STUDY

In this section, we implemented our proposed solution approach to address a pressing real-world issue. Our case study focuses on the urban center of Fortaleza, located in the Northeast region of Brazil (Figure 2). Fortaleza and its metropolitan area are home to nearly 4.2 million residents spread across 15 municipalities, boasting one of the highest population densities among major Brazilian cities. The city itself accommodates a fleet of 908,074 vehicles, with cars comprising 56% and freight vehicles 8% of the total.

The city center is characterized by narrow streets allowing parking on the right side. The dense concentration of commercial activities, including wholesale and retail, often leads to bottlenecks along these major roads. Unfortunately, the urban development of the city center has not kept pace with its economic growth. The result is a landscape dominated by contiguous buildings and narrow sidewalks, often illicitly occupied by retailers. Consequently, there’s insufficient space allocated for loading and unloading operations. Past efforts by the government to address this issue have been sporadic and disjointed, failing to tackle the root problem. As a consequence, freight vehicles engaged in loading/unloading activities within the city center may spend up to 9 hours or more to complete their tasks (Prata, Oliveira and Holanda, 2018).

Given this context, the application of decision support methodologies to mitigate these adverse impacts assumes paramount importance. Given that freight is typically managed by delivery personnel, our analysis excluded clients situated beyond a maximum permissible distance. Following the recommendation of Cepolina and Farina (2015), we set this maximum allowed walking distance at 450m. Four distinct scenarios of walking distances were delineated within the MILP model and the combined approach: 100m (Scenario 1), 200m (Scenario 2), 300m (Scenario 3), and 400m (Scenario 4).

For the MILP model, we employed the Cbc Solver (2024) in conjunction with the JuMP (2024) (Lubin and Dunning, 2015). Computational experiments were conducted on a PC equipped with an AMD Ryzen 3 3200U APU 3.5 GHz Dual-Core processor and 8GB of memory, operating on the Ubuntu 20.04 LTS platform. Notably, all scenarios were executed within negligible computational times (less than 1 second). A penalty factor (P) of 1000 was adopted in our experiments.

Spatial data containing the coordinates of 383 clients and 58 loading/unloading spaces were obtained from Fortaleza’s AMC (Municipal Transit and Citizenship Authority). Notably, the loading/unloading spaces provided by AMC are concentrated within less than 20% of our study area. However, there is a notable absence of spatial data delineating potential parking spaces across the entirety of the urban center. Figure 2 shows the location of the clients (orange polygons) and loading/unloading spaces (red dots), the road network and the neighborhoods (dark black polygons).

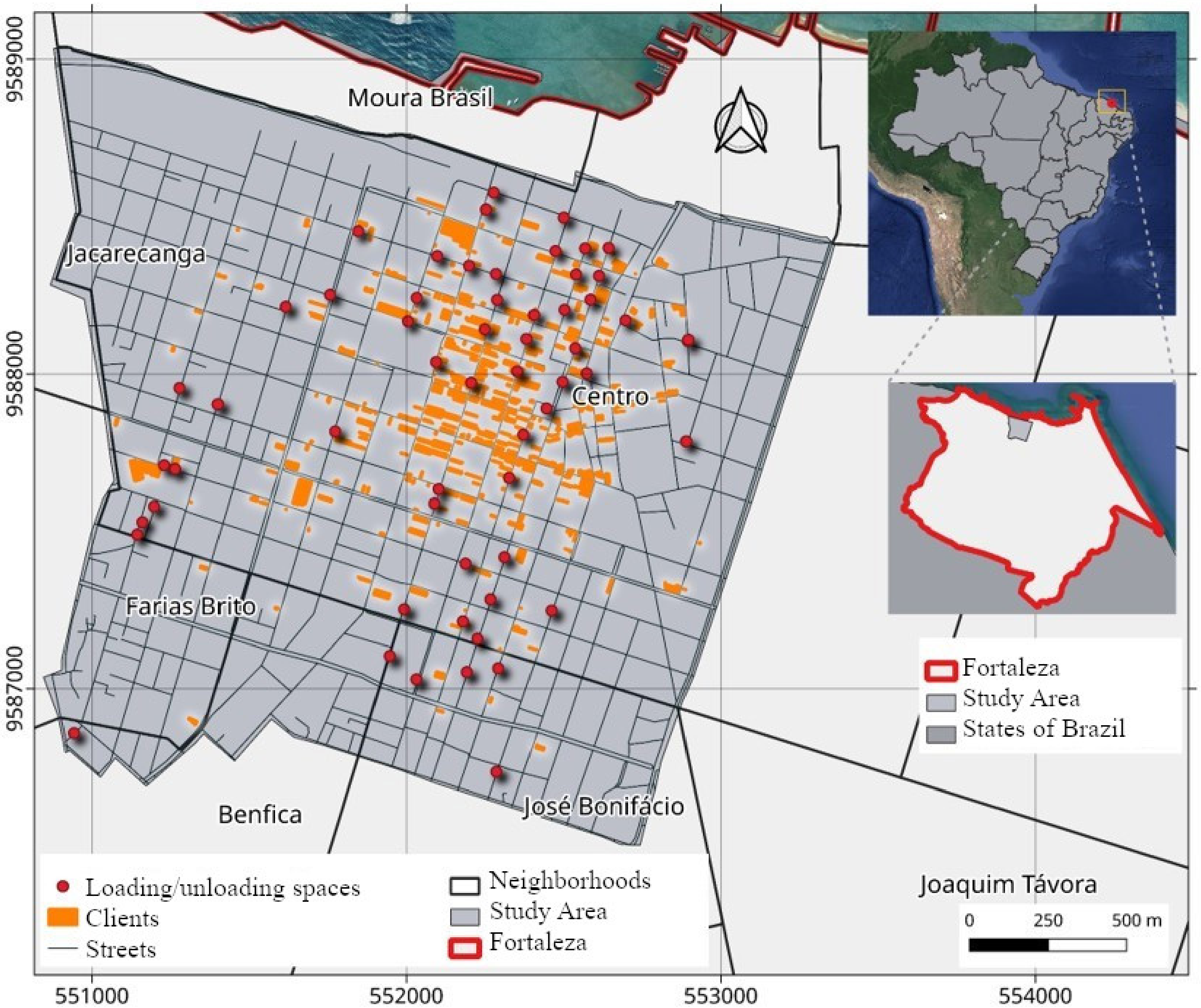

Figure 2. The map depicts the location of Fortaleza, Brazil, along with the distribution of clients and loading/unloading spaces within the city. Orange polygons represent the spatial distribution of clients, while red dots denote the locations of loading/unloading spaces.

Additionally, comprehensive spatial datasets encompassing the road network and urban blocks were procured from the Fortaleza in Maps online platform. These datasets played a pivotal role in determining distances between loading/unloading spaces and clients, as well as in assessing the proximity of these spaces to major roads.

The criteria detailed in Section 3.2, which guided the selection of optimal loading/unloading spaces within the combined approach, are visually depicted in Figure 3. In this depiction, blue dots denote spaces near clients with shorter frontal distances available for parking, transitioning in color from yellow to dark orange to represent increasing distances. In the southern section of the José Bonifácio neighborhood, clients have larger frontal distances available for parking.

Regarding the proximity to major roads, Figure 3 highlights this aspect with light pink segments indicating spaces nearer to major roads, while dark red segments represent spaces that are farther away. The southwestern area features spaces situated on roads closer to major roads.

Conversely, the Centro neighborhood at the heart of the study area exhibits a dense concentration of clients, evident by the gradual transition from dark orange hues towards lighter shades of yellow at its edges. This clustering of clients is aligned with the abundant availability of spaces in this vicinity, strategically positioned to meet substantial demand. Spaces farther from the study area's center with fewer clients nearby were not favored by the model, especially if the density of client's criterion held significant weight. Alternatively, if the frontal distance criterion were weighted more heavily, spaces in the southern part of the study area with larger frontal distances would be favored. Thus, there exists a trade-off between the density of clients within a 100-meter radius and the frontal distances of clients.

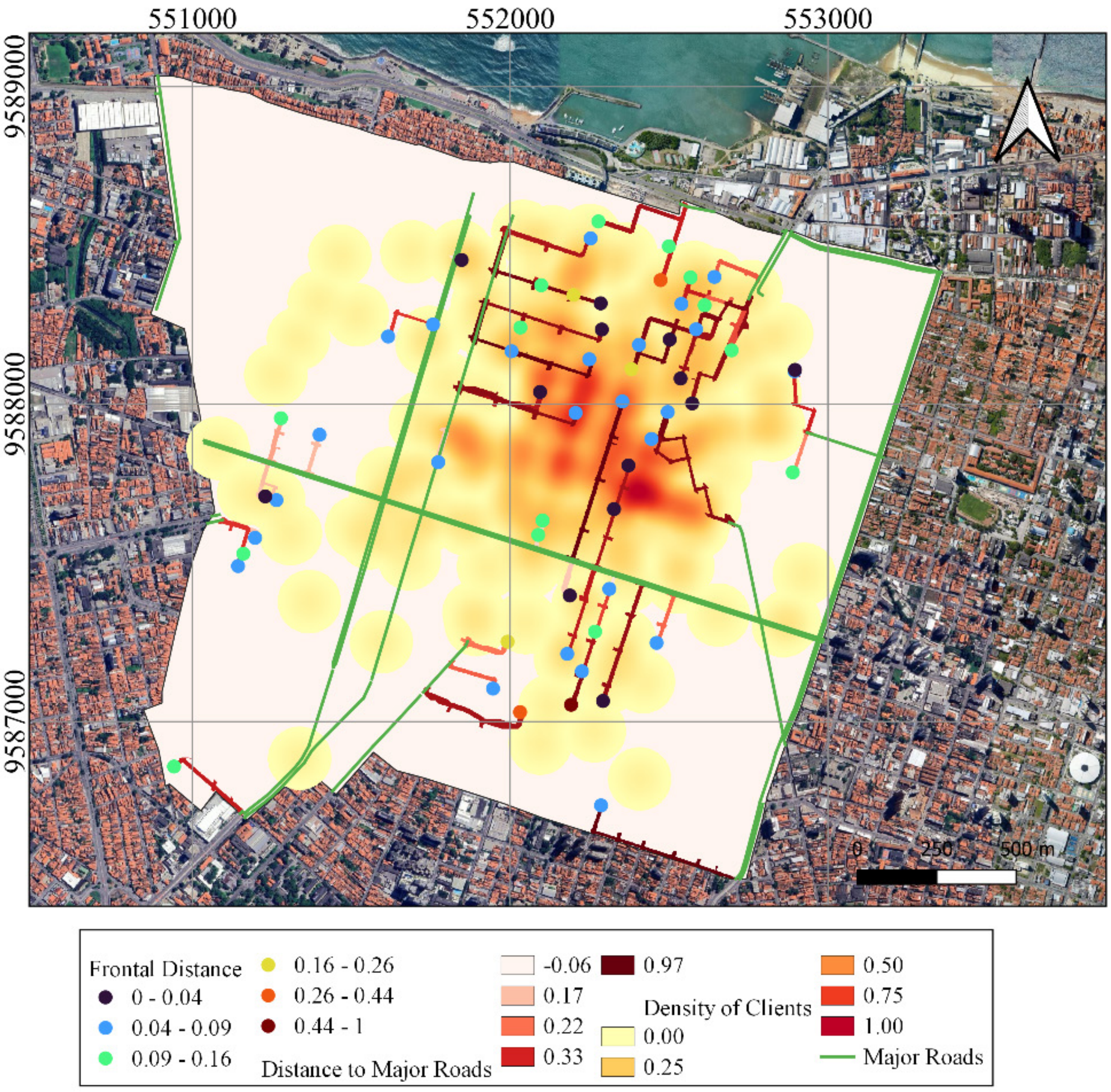

Figure 3. Criteria used to calculate the weighted average and determine the best loading/unloading spaces. Blue to dark red dots show the frontal distance of the spaces, the pink to red segments the roads that are closer or farther away from major roads and the yellow to dark red image the density of client's.

5. RESULTS AND DISCUSSIONS

5.1. Level of attractiveness MACBETH

From the online questionnaire administered via Google Forms, we gathered a total of 30 responses comparing the attractiveness of each criterion. Unfortunately, due to the time constraint we were unable to gather more responses. The respondents' profiles were diverse, comprising 3.1% professionals in transportation and logistics, 56.3% professors in the transportation field, 31.3% graduate and undergraduate students, and 9.3% individuals categorized as "others".

From the analysis of the three criteria, it was found that 20 out of 30 respondents indicated the density of clients within a 100m radius as the most important criterion, followed by the frontal distance of the clients and the distance of the loading/unloading spaces to the nearest major road.

The level of attractiveness of the most important criterion, i.e., the density of clients, was compared to the other two criteria using the MACBETH approach's qualitative scale of attractiveness between pairs. This scale ranged from N0 (Equivalent relevance) to N6 (Extremely relevant).

Figure 4 illustrates the frequency of responses for each level of attractiveness and criterion. In Figure 4A, the level of attractiveness of the density of clients compared to the frontal distance showed 9 responses each for weak (N2) and moderate (N3) levels. Both scenarios were tested, and since the final result was consistent, the weak level was chosen. Comparing the density of clients with the distance of the spaces to major roads, the questionnaire yielded 11 responses for a very strong (N5) level of attractiveness.

Figure 4B illustrates the frequency of responses regarding the level of attractiveness between the frontal distance and the distance from the spaces to the nearest major road. Finally, when comparing the frontal distance with the distance from the spaces to the nearest major road, the level of attractiveness moderate (N3) received the highest number of responses with 12 answers.

However, it's worth noting that the distance of the spaces to major roads was rated as very strongly relevant compared to the density of clients, which contradicted the classification of criteria previously presented. This discrepancy suggests that some respondents may not have fully understood the questionnaire or may have been inattentive when answering the questions, leading to inconsistencies in their responses. Nonetheless, the MACBETH software can handle such inconsistencies and understands that the numerical weights between the density of clients and frontal distance should be closer in value since their level of attractiveness is closer to equal relevance compared to the distance in value between the density of clients and the distance of spaces to major roads.

Based on these attractiveness scales, the density of clients was assigned a weight of 0.90, followed by the frontal distance with 0.58, and the distance to major roads with a weight of 0.10. Notably, there is a difference of 0.32 between the Density of Clients and the Frontal Distance, while the difference is higher for the Density of Clients and the Distance to major roads, with a value of 0.80.

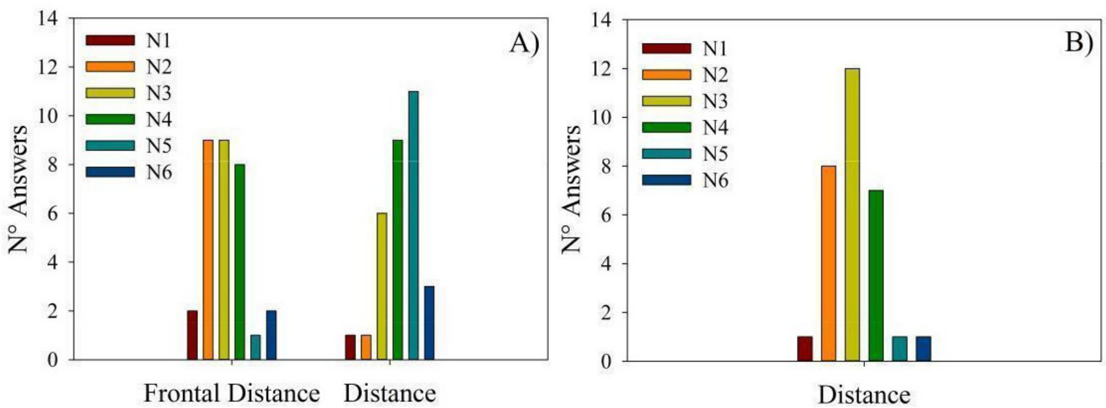

Figure 4. A) Level of attractiveness of the density of clients relative to the other criteria, B) level of attractiveness of the frontal distance relative to the other criteria.

5.2. Covered clients MILP and hybrid approaches

Table 2 describes the computational results for the MILP model and the combined approach. For both approaches, the optimal number of loading/unloading spaces varied from 52% (scenario 2 - 200m radius) to 60% (scenario 4 - 400m radius) of the 58 loading/unloading spaces available.

Table 2: Number of loading/unloading spaces per scenario and % of covered (Cov.) and uncovered (Uncov.) clients for the MILP and combined approaches.

Radius (m)	Spaces	Cov. MILP	Uncov. MILP	Cov. Combined	Uncov. Combined
100	32	55.09	44.91	56.66	43.34
200	35	74.67	25.33	85.38	14.62
300	34	86.42	13.58	93.99	6.01
400	30	95.56	4.44	95.82	4.18

It's noteworthy that for the 200m radius (scenario 2), the percentage of covered clients increased by approximately 10% when employing the combined approach compared to solely utilizing the MILP model. Similarly, in scenario 3 with a 300m radius, there was an 8% rise in the number of covered clients with the combined approach compared to the MILP model. However, for the shortest and longest walking distances (100m and 400m), the percentage of covered and uncovered clients remained largely consistent between both approaches.

Considering a walking distance of up to 400m from the loading/unloading spaces to the clients, approximately 95% of the clients would be covered by these spaces. Despite nearly full attendance in this scenario, service levels are diminished due to increased operational time for freight delivery caused by longer walking distances for the drivers.

Also, considering a maximum walking distance of 100 m, as suggested by Dablanc (2009) and Santos Junior and Oliveira (2020), only 56% or 214 out of 383 clients would be covered by these spaces. This indicates both low accessibility and level of service. To enhance accessibility, the maximum allowed distance between establishments and unloading spaces would need to be reduced to 75 m, according to Santos Junior and Oliveira (2020). While this study analyzed distances starting from 100 m, a scatterplot was plotted using Table 2, and considering the percentage of covered clients from the combined MILP and MACBETH approach (Figure 5), were the predicted coverage for a 75 m distance would be 51% of the client's.

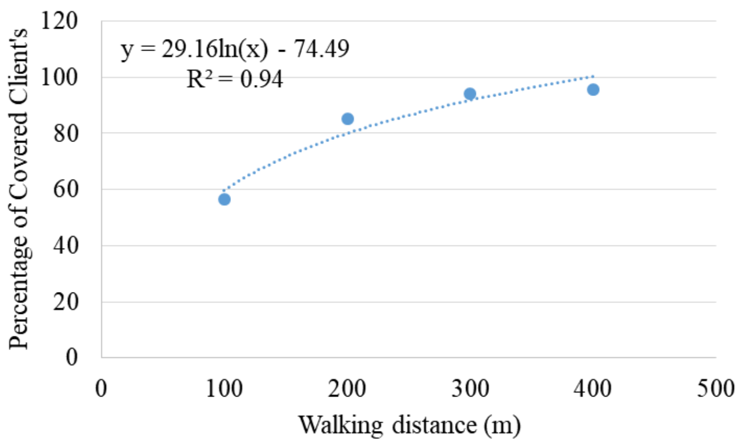

Figure 5. Percentage of covered client's for the MILP and combined approaches.

Furthermore, the number of daily trips was not estimated in this study, hence the demand cannot be accurately analyzed, considering that there might be multiple trips for each client. In the study conducted by Silva et al. (2024), they determined that the loading/unloading spaces cover only 18% of the estimated demand in São João del Rei. Unfortunately, for our study, there is a lack of available data indicating the number of deliveries conducted for each establishment.

Although the number of loading/unloading spaces for each scenario remained constant across both approaches (as shown in Table 2), the spatial distribution of these spaces differed significantly between the MILP model and the combined approach, as depicted in Figure 6. Within this figure, blue dots represent loading/unloading spaces disregarded by both the MILP and combined methods. These spaces are predominantly located in the extreme western, southern, and northern regions of the study area, where client density is notably sparse. Meanwhile, the dots transitioning from white to dark red signify the varying numbers of clients served by each loading/unloading space.

Under the MILP model, selected spaces were predominantly clustered in the Centro and Jose Bonifacio Neighborhoods. While only three spaces covered up to 16 clients in the Jose Bonifacio neighborhood, 27 spaces in the Centro neighborhood served a substantial clientele, with three of them covering up to 238 clients each.

In contrast, the combined approach featured only two spaces in the Jose Bonifacio neighborhood, with approximately 94% of spaces concentrated in the Centro neighborhood. Here, five spaces covered up to 238 clients each. This disparity in spatial distribution is attributed to the inclusion of the Density of Clients criterion, with about 98% of clients situated in the Centro neighborhood.

Notably, the number of covered clients per space was remarkably similar for both approaches, as evidenced by the data in Table 2 for the 400m radius. For the MILP model 95.56% of the clients were covered by the selected spaces, whereas for the combined approach 95.82% of the clients. While both approaches covered a comparable proportion of clients, there was a distinct spatial preference in their selection of loading/unloading spaces. The MILP model favored spaces in the northern and southern regions of the study area, whereas the combined approach predominantly chose spaces situated in the central portion of the study area.

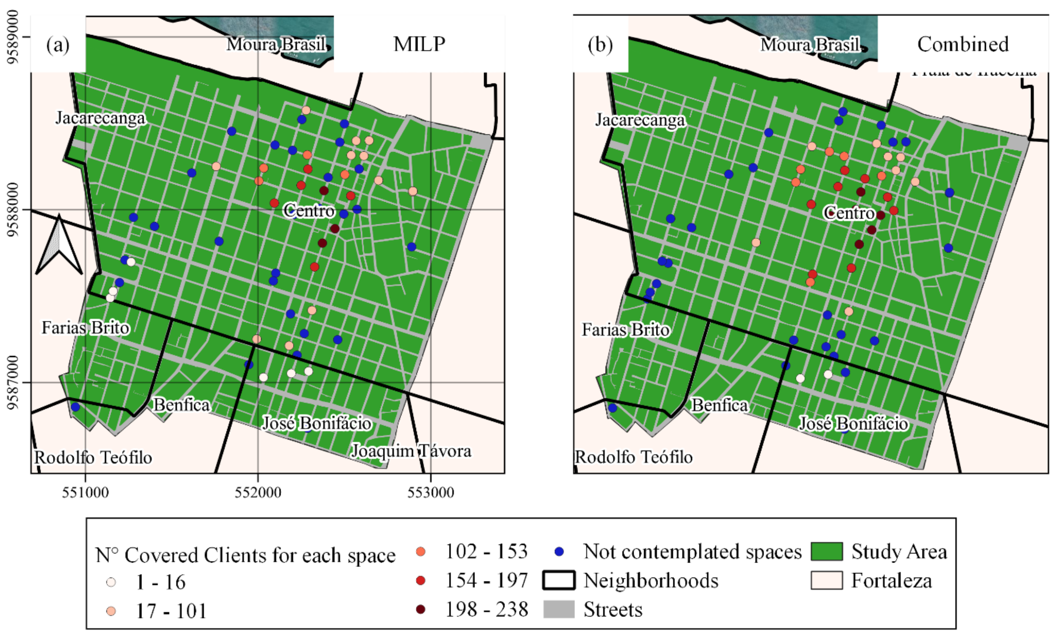

Figure 6. Location of the selected loading/unloading spaces and the number of covered clients (white to dark red dots) for the (a) MILP and (b) combined approaches, considering a radius of 400m.

5.3. Local Moran index

An autocorrelation analysis was conducted based on the spatial distribution of loading/unloading spaces, employing the local Moran Index. Across both the combined approach and the MILP model, the index ranged from 0.88 to 0.98, indicating a pronounced spatial autocorrelation in the density of covered clients across all walking distance scenarios.

Notably, the percentage of covered clients exhibited more significant disparities in scenario 2, as outlined in Table 2. Consequently, we concentrated our autocorrelation analysis on this particular scenario. Figures 7 and 8 showcase the significance ($p < 0.05$) and Moran's clusters for scenario 2 (200m walking distance) for both the MILP and combined approaches, respectively.

In interpreting these results, the presence of high-high (red) and low-low (blue) road segments signifies that the segment under scrutiny shares similar values with its neighboring areas, indicating spatial clustering (Anselin, 2005). Within the MILP model, a conspicuous high-high cluster is identified in the Centro neighborhood, denoting a notable concentration of clients covered by the loading/unloading spaces in this vicinity (Figure 7). This cluster encompasses approximately 10% of the road segments within the study area.

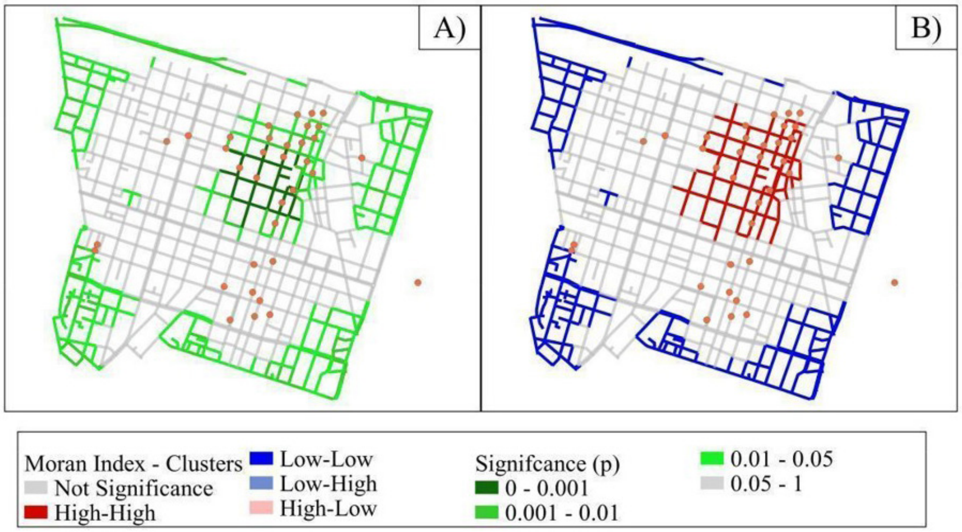

Figure 7. A) LISA Significance and B) Moran's Clusters for the mean density of covered clients for each road segment, considering Scenario 2 and the MILP approach.

On the other hand, the blue-shaded areas denote clusters of roads lacking coverage from loading/ unloading spaces, indicating a lower level of service in these zones (Figure 7). However, owing to the spatial arrangement of loading/unloading spaces, approximately 38% of road segments exhibit a notably low density of covered clients. These clusters persist across scenario 3 for both the MILP and combined approaches.

In the context of the combined approach, only the high-high cluster is deemed significant, encompassing roughly 11% of the study area (Figure 8). This outcome stems from the method of space selection for loading/unloading, which prioritizes locations with the highest weighted average values. As the density of clients carries the greatest weight, spaces situated farther from clients were excluded from analysis, resulting in few clients outside the central region not accounted for by the combined approach.

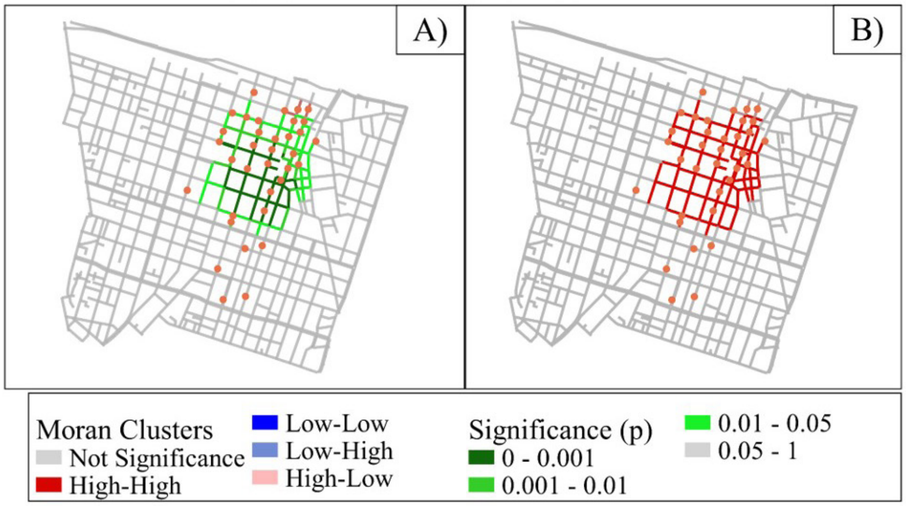

Figure 8. A) LISA Significance and B) Moran's Clusters for the mean density of covered clients for each road segment, considering Scenario 2 and the hybrid approach.

5.4. Data and model limitations

To comprehensively understand the intricacies of the study location, conducting a survey with both retailers and customers is imperative. This approach would unearth additional pertinent criteria for inclusion in the analysis, such as street width, traffic volume, pavement condition, and delivery duration and timing. Moreover, the absence of spatial data at this analytical scale poses a challenge in incorporating other relevant factors into the models.

In relation to the combined approach, determining the level of attractiveness necessitates considering all stakeholders involved in the decision-making process. Furthermore, analyzing variations in attractiveness levels would enhance understanding of how weights influence the selection of optimal loading/unloading space locations. Expanding the scope to include all potential parking spaces within the urban center, rather than solely relying on registered spaces provided by the AMC, is advisable. This is crucial as the registered spaces predominantly concentrate in the central region, leaving a mere 11% to 18% of the study area covered by loading/unloading spaces.

While the MILP model efficiently allocates clients to loading/unloading spaces with minimal computational effort, it overlooks key aspects of the decision-making process in city logistics. Traditional integer linear programming formulations for such problems often rely solely on Euclidean distances to establish cover relations. However, as mentioned earlier, these conditions prove necessary but insufficient for addressing the complexities inherent in the studied problem environment.

6. CONCLUSION

In this research, an innovative combined MILP, MCDA, and GIS approach is presented to determine the best location of loading and unloading spaces for urban freight in the cities. The proposed approach was validated in a real-world application in Fortaleza, Brazil. To the best of the authors' knowledge, there are no other similar approaches for this purpose in the available literature.

Taking several real-world scenarios into account, we were able to find the location of loading/ unloading spaces considering multiple criteria and spatial attributes. In practice, for different user demands, these characteristics of the solutions can be explored, improving the efficiency of real systems.

The developed solution approach combines mathematical programming (for the determination of the optimal number of loading/unloading spaces), the MACBETH method (for the consideration of multiple criteria), and spatial analysis (for the evaluation of the solutions in a GIS framework). The spatial statistical analysis has demonstrated to be efficient in pointing out the service level in the road segments in the neighborhood of the selected facilities.

Concerning the limitations of this research, we can emphasize the following issues. First, we used the location of loading/unloading spaces for urban freight operations in the city center as registered by the municipality. With better localization of these parking spaces, higher coverage of the clients could be achieved. Second, regarding the application of MACBETH, a greater number of questionnaires could be administered. Furthermore, a sensitivity analysis could be conducted to evaluate how changes in the criteria weights or evaluations affect the overall ranking or scoring of alternatives. Third, our proposal has not considered several characteristics that arise in real-world scenarios, such as transportation costs, pollutant emissions, traffic simulation, and the dynamic occupation of loading/unloading spaces.

In our proposal, the candidates for loading/unloading spaces are input for our multicriteria decision approach. As a natural development of this research, the authors are currently working on the development of a methodology that optimizes this selection, aiming to generate better solutions for real-world scenarios.

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Supplementary Material

Supplementary material accompanies this paper.

Localização das vagas para carga e descarga em áreas urbanas

This material is available as part of the online article from https://doi.org/10.58922/transportes.v32i3.2970