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Characterization of urban mobility in Bogota: A spatial autocorrelation analysis

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Abstract: This paper studies the variables influencing urban mobility in Bogota's urban planning zones (UPZs) through spatial autocorrelation analysis. Initially, data from various databases were compiled, covering 13 variables across 111 UPZs. A descriptive analysis identified significant variables, revealing a positive skewness trend. Higher social strata (4, 5, and 6) correlated with better mobility indices and more automobiles per family. The Moran's Index showed strong spatial autocorrelation in mobility indices, indicating that nearby UPZs have similar mobility patterns. Areas like Suba and Usaquén, with better infrastructure, showed higher mobility indices, while Ciudad Bolivar and Usme had poor infrastructure and low mobility. The study highlights the correlation between mobility and factors like social strata, automobile numbers, and infrastructure, providing a foundation for future transport and urban planning policies.

Keywords: Spatial autocorrelation, Moran's Index, mobility, charging stations

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1. Introduction

The adoption of urban mobility is constrained by a lack of specialized infrastructure, particularly in the number of charging stations. According to projections, the existing electrical grid is insufficient to support one charging station per family nucleus over the next seven years, (Acosta et al., 2023). This makes it imperative to optimize the location of public charging stations within existing infrastructures, such as public parking lots, shopping centers, and universities, among others, in order to reduce travel time and increase coverage.

In addition to this need, governmental entities have been compelled to formulate policies focused on sustainable mobility to address issues of transit, transportation, and traffic, (Álvarez Medina & Marquina Sánchez, 2023; Bernal Alvarado, 2023). The primary aim of these initiatives is to reorient urban planning strategies to improve the quality of life for citizens. Historically, there has been a predominant trend towards individual mobility, to the detriment of integrated public and collective transportation systems. This circumstance has exacerbated challenges in traffic management, particularly during peak hours, which generally coincide with the start and end times of work, academic, and commercial activities.

Over the past century, mobility has been predominantly influenced by vehicles powered by internal combustion engines that use fossil fuels derived from petroleum, such as gasoline, (Alvarez García, 2022; Hernandez, 2021). This mobility model generates emissions of particulates, carbon monoxide, carbon dioxide, and other toxic gases, which have adverse environmental impacts and contribute to the phenomenon of the greenhouse effect (Ankathi et al., 2022; Landa Barra, 2022). These environmental impacts have precipitated the formulation of international agreements and conventions such as the United Nations Framework Convention on Climate Change (1994), the Kyoto Protocol (1997), and the Paris Agreement (2016), which was supplemented at the Glasgow summit in 2021, (García Lupiola, 2021; Dormido et al., 2022).

In response to these global environmental concerns, Colombia has implemented strategies such as the National Electric Mobility Strategy (NEMS) and the National Energy Plan 2020-2050 through various ministries and agencies (Landa Barra, 2022; UPME, 2023; Vargas Marín, 2021). These initiatives aim to promote the adoption of electric vehicles (EVs) and align with the global trend towards more sustainable and eco-friendly mobility. The Law 1844 of 2017, which ratifies the Paris Agreement together with other legislation, it has guided the transport sector towards more sustainable practices, as it is one of the major energy consumers.

The Moran's Index has established itself as a crucial tool in the field of geospatial research, offering a robust metric to evaluate spatial autocorrelation in a dataset (Celemín, 2009; Vargas et al., 2021). In the realm of urban mobility, the Moran's Index is employed to identify and quantify spatial patterns in the distribution of variables related to transit, such as vehicle density. Its use in this context has enabled the discovery of areas of high congestion in various cities, providing authorities with a geospatial evidence base for decision-making (Li et al., 2022). By unravelling the autocorrelated nature of phenomena related to mobility, the Moran's Index serves as a nexus between physical geography and urban planning, offering valuable insights for the design of more effective and sustainable interventions, (Xu et al., 2021).

As the world shifts towards more sustainable mobility solutions, the transition to electric automobility has gained increasing importance, (Rindone, 2022; Sæther, 2022). In this context, the Moran's Index has proven to have particular relevance. By analysing the spatial patterns associated with the adoption and use of electric vehicles, this index enables the identification of areas with higher concentrations, as well as zones where charging infrastructure is either insufficient, oversized, or prone to expansion. This understanding of spatial patterns guides both public and private investment in charging infrastructure, helps ensure equity in access to clean technologies, and fosters the creation of an urban ecosystem conducive to the expansion of electric automobility (Li et al., 2022). Thus, the integration of spatial statistical tools like the Moran's Index in research on charging stations for electric vehicles allows for the development of a more informed and effective roadmap for the introduction of electric vehicles in Bogota D.C.

In the present paper, a descriptive analysis is conducted on variables affecting mobility, how they are interrelated, and the degree of spatial autocorrelation they exhibit, bearing in mind the first law of geography: *everything is related to everything else, but near things are more related than distant things*, (Siabato& Guzmán-Manrique, 2019; Tobler, 1970). Data from open sources like OpenStreetMap and National Administrative Department of Statistics (DANE as abbreviated in Spanish) are used in the context of Bogota. The focus is on identifying priority areas where, under current conditions, it is essential to improve infrastructure to encourage the adoption of electric mobility.

2. Methodology

The methodology employed began with the collection of information aimed at characterizing the city of Bogota in aspects related to mobility. These include high-concentration centers of people such as universities, hospitals, and both zonal and metropolitan shopping centers, as well as fuel service stations and the distribution of motorcycles and automobiles. All of this data was analyzed in terms of Zonal

Planning Units (UPZ as abbreviated in Spanish). The sources of information come from DANE, the District Secretariat of Education (SED as abbreviated in Spanish), the District Secretariat of Planning (SDP as abbreviated in Spanish), Open Data Bogota (IDECA as abbreviated in Spanish) and OpenStreetMap.

The second step involved descriptive analysis aimed at identifying significant variables that contribute to the study. This analysis included the mobility index and the proportion of automobiles per UPZs. The third and final step focused on the analysis of spatial autocorrelation using the Moran's Index.

Among the techniques and tools used, RStudio 2023.03.0 Build 386, (Dorie et al., 2023; Wickham & Bryan, 2023), Geoda, and QGIS were employed for the descriptive statistical processes. These programs allowed for the exploration of measures of central tendency, measures of variability, scatter plots, and histograms. As for spatial autocorrelation, Moran's Index was used as the technique for spatial autocorrelation analysis. This metric aims to identify patterns of spatial similarity or dissimilarity in the data, and the results were represented through spatial autocorrelation maps.

3. Baseline information

The variables and data used in the present study comprise a total of 13 variables and 111 records for each variable, corresponding to the UPZ of 19 out of the 20 localities that make up the city of Bogota. In this research, locality 20, corresponding to Sumapaz, it was excluded because it is predominantly a rural area with low vehicular impact. Likewise, UPZ 117, corresponding to the Airport area, was excluded due to its unique spatial conditions. Table 1 provides a summary of the variables used and their respective sources.

The mobility index (MI) has been determined since 2012, based on the integration of 8 selected variables from the Mobility and Multipurpose Survey of 2011. These variables include population, number of automobiles, number of motorcycles, number of bicycles, number of trips made on public transportation, number of trips made by individuals with disabilities, average travel time, and per capita income. The defined ranges for this variable are detailed in Table 2, (Índice de movilidad para Bogotá, 2013).

With vLM representing very low mobility, LM indicating low mobility, mLM denoting medium-low mobility, mHM signifying medium-high mobility, HM standing for high mobility, and vMH designating very high mobility.

The infrastructure variable (INFR) is defined based on discrete variables that represent whole numbers, specifically parking lots (Par), health centers (HC), universities (Uni), fuel stations (FS), commercial centers (CC), supermarkets (Sup), and parks (Park). The result of the normalized weighted sum is shown in Equation (1).

$$I_{INFR} = \frac{Par + HC + Uni + FS + CC + Sup + Park}{INFR_{Max}} \quad (1)$$

Thus $0 \le I_{INFR} \le 1$, where values close to zero represent areas with scarce infrastructure, while values close to 1 represent areas with the abundant possible infrastructure for each UPZ.

Table 1. List of variables used, DEM, MOV, INFR indicates the type of variables, demographic, mobility and infrastructure, respectively.

Variables	Symbols	Type	Source	Ref.
socioeconomic stratum	SS	DEM	Secretaría Distrital de planeación	(SDP, 2023)
# population	Pop	DEM	DANE	(DANE, 2023)
# family nucleus	FN	DEM	DANE	(DANE, 2023)
# Automobiles	Aut	MOV	Bogotá como vamos	(IDECA, 2023)
# Motorcycles	Mo	MOV	Bogotá como vamos	(IDECA, 2023)
Mobility index	MI	MOV	Secretaría Distrital de planeación	(SDP, 2023)
# parking	Par	INFR	Bogotá mi ciudad	(Bogotá 2023; OSM 2023)
# health centers	HC	INFR	Secretaría de Salud	(SDS 2023; DAB2023)
# universities	Uni	INFR	Bogotá y sus universidades	(IDECA 2023; OSM 2023)
# fuel stations	FS	INFR	OpenStreetMap	(IDECA 2023; OSM 2023)
# commercial centers	CC	INFR	OpenStreetMap datos abiertos	(IDECA 2023; OSM 2023)
# supermarket	Sup	INFR	OpenStreetMap datos abiertos	(IDECA 2023; OSM 2023)
# parks	Park	INFR	OpenStreetMap datos abiertos	(IDECA 2023; OSM 2023)

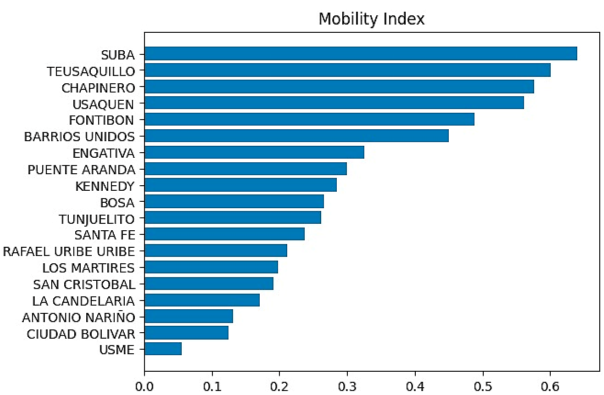
Table 2. Mobility index ranges.

vLM	LM	mLM	mHM	HM	vHM
0≤MI< 0.13	0.13 ≤ MI<0.25	0.25 ≤ MI<0.31	0.31 ≤ MI<0.36	0.36 ≤ MI<0.62	0.62 ≤ MI≤1

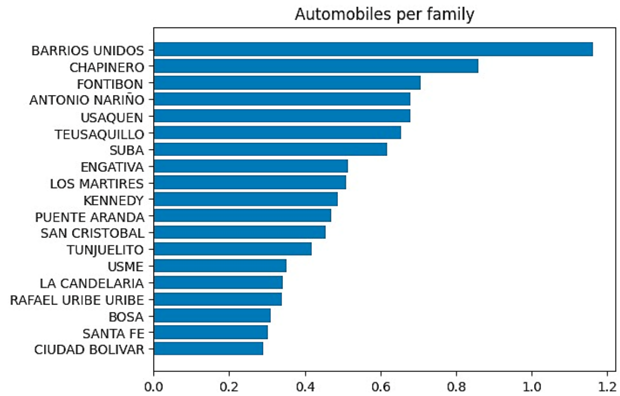
4. Descriptive analysis

The basic statistical analysis provides information about the minimum value, maximum value, quartiles, mean, median, and standard deviation of the variables studied. This information allows for an initial numerical description of the variables. The summary of these results is presented in Table 3. It is noteworthy that the skewness coefficient is positive for all variables, indicating a tendency toward a positive bias, which is related to mean values that are higher than median values. Additionally, interpretations of these findings are left to the reader.

In Figure 1a, the relationship between the MI and various neighborhoods in Bogota is illustrated. It is observed that the UPZs with the best MI are located in the neighborhoods of Suba, Teusaquillo, Chapinero and Usaquén. In contrast, Usme and Ciudad Bolívar exhibit the lowest MI.



(a)



(b)

Figure 1. Mobility index, and (b) automobiles per family by locality.

On the other hand, Figure 1b displays the number of automobiles per family nucleus according to the neighborhoods. Notably, the highest number of automobiles per family nucleus is found in Barrios Unidos and Chapinero, while Ciudad Bolívar and Santa Fe have the lowest proportion.

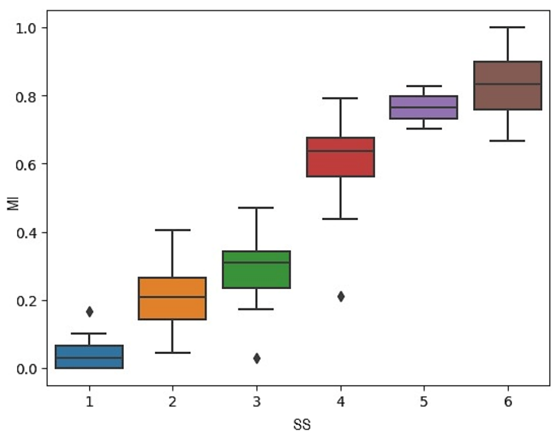
Additionally, bivariate relationships can be explored in the analysis. In Figure 2a, the box plot shows the MI as a function of socioeconomic stratum. It is noteworthy that socioeconomic strata 4, 5, and 6 are associated with the highest mobility indices, with $MI > 0.36$, whereas strata 1 and 2 are linked to lower mobility indices, with $MI < 0.36$. In Figure 2b, the relationship is shown between socioeconomic stratum

Table 3. Statistics of central tendency and variability.

	Min.	1erQ.	Median	Mean	SD	kurtosis	skewness	3erQ.	Max.
SS	1	2	3	2.91	1.18	0.45	0.68	3.5	6
Pop	1169	31012	54369	71525.4	58251	3.24	1.53	101097	305907
FN	365	13002	20149	26869.13	20964	2.84905	1.45402	36838	105480
Aut	132	4647	10937	13882	12818	3.47846	1.69	17560	69515
Mot	108	3802	8948	11359	10487	3.48	1.69	14367	56876
MI	0	0.20	0.31	0.36	0.23	-0.22	0.74	0.5	1
Pa	1	4	7	7.17	4.30	-0.3489	0.456	10	20
HC	0	0	1	1.23	1.37	0.97	1.28	2	5
Uni	0	0	0	0.91	1.78	15.17	3.41	1	12
FS	0	1	2	2.86	2.15	-0.94	0.48	5	7
CC	0	0	1	1.42	2.24	11.45	3.10	2	13
Sup	0	3.5	7	9.17	7.32	1.16	1.25	14	33
Park	0	2	4	4.45	2.88	3.93	1.54	6	17

and the number of automobiles per family nucleus, it is observed that the highest number of automobiles is found in socioeconomic strata 4, 5, and 6. Additionally, higher outlier values are noticed in strata 3 and 4.

There is also a notable direct relationship between socioeconomic stratum, the number of automobiles per family nucleus and the mobility index. That is, as the socioeconomic stratum increases, so does the proportion of automobiles per family nucleus as well as the quality of mobility. This correlation provides significant insight for the planning of charging stations, especially in the context of the adoption of electric vehicles in Bogota city.



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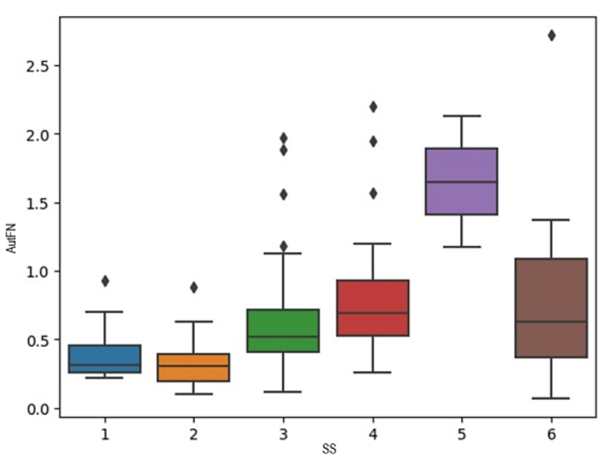
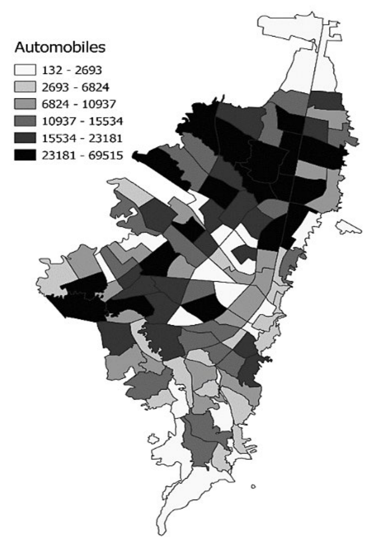


(b)

Figure 2. (a) Stratum with mobility index and (b) stratum with automobiles per family nucleus.

Figure 3a shows a map that illustrates the spatial distribution of the number of automobiles per UPZs in Bogota city. On this map, UPZs with the highest number of automobiles (44.65%) are primarily located in the neighborhoods of Suba, Usaquén, Chapinero and Engativá. Conversely, the UPZs with the lowest number of automobiles ($8,84\%$) are in Ciudad Bolívar, Usme, San Cristóbal and Rafael Uribe Uribe neighborhoods. On the other hand, Figure 3b shows the distribution of the MI across the UPZs. At least 22 UPZs, mainly in the neighborhoods of Suba, Chapinero, Usaquén, Fontibón and Teusaquillo exhibit a high MI. In contrast, the UPZs in Ciudad Bolívar, Usme, San Cristóbal, Santa Fe and Rafael Uribe neighborhoods who display low mobility indices. The UPZs 60, 63, and 117 were not included in this analysis due to their special characteristics. In both figures, it shows the direct relationship between the number of automobiles and the MI in the same UPZs. That is, UPZs with a higher number of automobiles also tend to have a high MI, and these are correlated with the higher socioeconomic stratum (4, 5, and 6). This finding could have significant implications for urban planning and mobility management in Bogota city.



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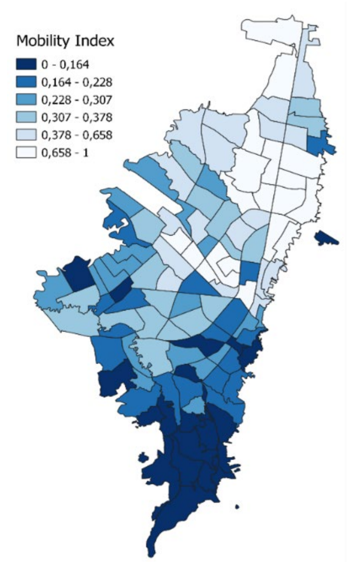


(b)

Figure 3. (a) Automobiles and (b) mobility index for UPZs.

Finally, to identify variables that are most strongly related to each other, an analysis employing the coefficient of determination R^2 and the rank correlation coefficient (r) are used. The range of values that (r) can take is between $-1 \le r \le 1$, where values close to zero indicate an absence of linear correlation between the two variables in question. On the other hand, an r of 1 or -1 signifies a perfect direct or inverse correlation, respectively. If $-0.5 \le r \le 0.5$, a weak level of correlation is considered. For $-1 \le r < -0.5$ or $0.5 < r \le 1$, strong levels of correlation are considered (Xiao et al., 2016). This analysis is important to understand how different variables are interrelated, which is useful to develop policies and strategies in urban planning and mobility.

In Figure 4, correlations between study variables are presented. Strong correlations are observed in various combinations of variables: population to family nucleus (0,99), MI to socioeconomic stratum (0,88), family nucleus to automobiles (0,58), fuel stations to supermarkets (0,54), population to automobiles (0.53) and healthcare centers to fuel stations (0,52). Regarding negative correlations, the following relationships are found: population to universities (-0,26), suggesting that universities tend to be located in UPZs with lower average population density; socioeconomic stratum to population (-0,23), indicating that as population increases, the socioeconomic stratum tends to be lower; family nucleus to universities (-0,22) and socioeconomic stratum to family nucleus (-0.18).

Figure 4. Correlation of variables.

Variables with practically null correlations are observed, indicating a lack of linear relationship between them; MI to family nucleus (0.0044) and population to commercial centers (0.0038). The aim of this analysis is to investigate which variables contribute significatively to the estimation of the number of automobiles in Bogota city. This analysis is crucial for a better understanding of the factors that impact mobility, with the goal of designing more effective public policies in this area.

5. Spatial autocorrelation

Spatial autocorrelation provides a framework for examining the relationships or variations between the values of a specific variable across different geographical locations. Various indices and methods are designed to quantify this spatial autocorrelation, among which the Moran's index (I) is the most widely used. This index is based on the comparison of the values of a variable at a given location with the values at neighboring locations, and it is formally defined as:

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

where *n* is the total number of spatial observations, *W* is the total sum of the spatial weights, w_{ij}, x_i and x_j are the values of the variable of interest for observations *i* and *j*, and $\bar{x}$ is the mean of the variable of interest. The spatial weights w_{ij} are typically defined based on the geographical proximity between observations *i* and *j*. The index ranges from -1 to 1, where a value close to 1 indicates strong positive spatial autocorrelation, a value close to -1 indicates strong negative spatial autocorrelation, and a value close to 0 suggests a random spatial distribution (Siabato & Guzmán-Manrique, 2019; Lopez, 2021).

Moran's Index can be both global and local. The global Moran's Index provides a single measure that summarizes the spatial autocorrelation for the entire dataset, offering an overall view of the trend in the spatial distribution of a variable. In contrast, local Moran's Index (LISA, an acronym for Local Indicators of Spatial Association) breaks down the spatial autocorrelation into a measure for each location, allowing to identify of *hot and cold spots*, where the variable of interest shows significantly high or low autocorrelation. While the global index is useful for understanding spatial patterns on a broader scale, the local index allows for a more detailed and geographically differentiated analysis, which is especially useful for identifying areas requiring specific attention in urban planning studies and other applied fields (Siabato & Guzmán-Manrique, 2019; Chaparro H. I., 2023).

The local Moran's index was implemented using a first-order queen method for the MI. Figure 5 displays the Moran's index for the MI, which has a value of $I = 0.656$. This result indicates strong spatial autocorrelation among the first-order neighboring UPZs. This figure is divided into four quadrants that interpret different scenarios of spatial autocorrelation:

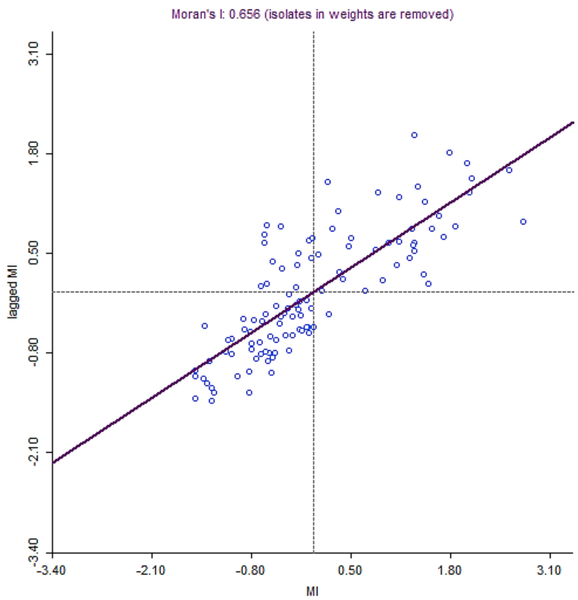


Figure 5. Moran's index global for mobility index.

Quadrant I: In this, the UPZs that exhibit high mobility indices $MI < 0.25$, are located and the UPZs are surrounded by neighbors that also have high mobility indices. This is a case of positive spatial autocorrelation: high values near high values.

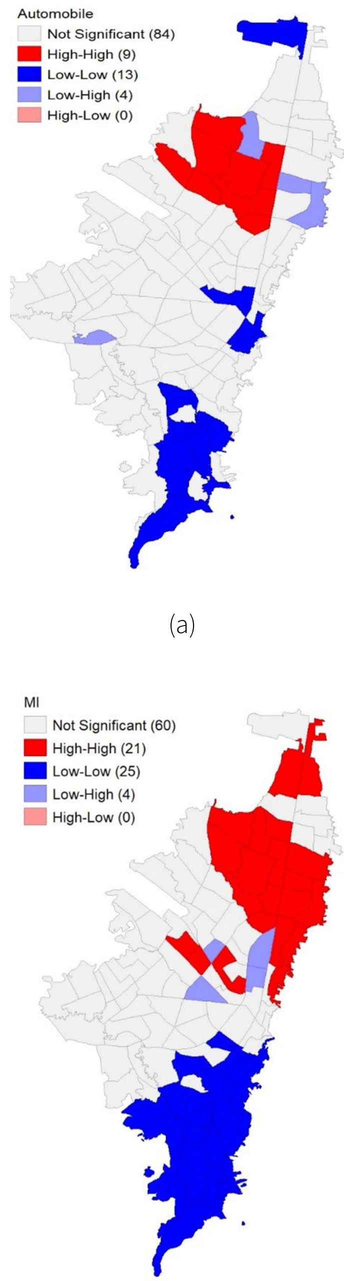
Quadrant II: In this, UPZs with low mobility indices $MI < 0.25$ are surrounded by neighbors with high mobility indices. This could indicate areas that are atypical or could benefit from improvements in infrastructure.

Quadrant III: This contains UPZs with low mobility indices that are surrounded by neighbors who also have low mobility indices. This is another case of positive spatial autocorrelation, but in this case, it is low values near low values.

Quadrant IV: This includes UPZs with high mobility indices that are surrounded by neighbors with low mobility indices. This could represent areas that are functioning well in terms of mobility but are surrounded by areas requiring attention.

The high value of Moran's index and the distribution of UPZs in these quadrants provide valuable information for urban planning, allowing to identify areas that could benefit from specific interventions to improve mobility.

In Figure 6a, the variable *automobiles* show an *I = 0,230*, indicating a medium level of spatial Specifically, UPZs with a higher number of automobiles that are surrounded by UPZs neighbors with similar characteristics (*high - high*) are observed in 9 UPZs located in Suba, Engativá and Barrios Unidos. UPZs with a lower number of automobiles that are surrounded by UPZs neighbors with similar characteristics (*Low-Low*) are observed in 13 UPZs Usme, Santa Fe, La Candelaria, San Cristóbal and Rafael Uribe. UPZs with a lower number of automobiles but surrounded by PUZs neighbors with a higher number of automobiles (*Low-High*) are observed in 4 UPZs located in Suba, Bosa and Usaquén. Finally, no such UPZs with a higher number of automobiles that are surrounded by UPZs neighbors with a lower number of automobiles (High-Low).



(a)

(b)

Figure 6. Moran's index for (a) automobiles and (b) mobility index.

In Figure 6b, a spatial autocorrelation map for the mobility index reveals: UPZs with *MI > 0,36* surrounded by UPZs neighbors with *MI > 0,36*, (*High-High*) are observed in 21 UPZs located in Suba, Chapinero, Usaquén, Fontibón, Teusaquillo, and Barrios Unidos. UPZs with *MI < 0,25* surrounded by UPZs neighbors with *MI < 0,25*, (*Low-Low*) are observed in 25 UPZs in Ciudad Bolívar, Usme, Antonio Nariño, Rafael Uribe Uribe, Santa Fe, San Cristóbal and Tunjuelito. UPZs with *MI < 0,25* but surrounded by neighbors with *MI > 0,36*, (*Low-High*) are observed in 4 UPZs in Engativá, Teusaquillo, Puente Aranda and Barrios Unidos. Finally, no such UPZs with *MI > 0,36* that are surrounded by UPZs neighbors with *MI < 0,25*, (High-Low).

Regarding the bivariate local Moran's for automobiles and the MI, with *I = 0,237* as shown in Figure 7, a medium level of spatial autocorrelation is indicated. Specifically: UPZs with *MI > 0,36* and a higher number of automobiles, surrounded by neighbors with similar characteristics (*High-High*), are observed in 10 UPZs located in Suba, Usaquén and Barrios Unidos. UPZs with *MI < 0,25* and a lower number of automobiles, surrounded by neighbors with similar characteristics (*Low-Lo*), are observed in 10 UPZs located in Usme, Santa Fe, La Candelaria, and Rafael Uribe. UPZs with *MI < 0.25* but a higher number of automobiles (*Low-High*) are observed in 3 UPZs located in Bosa and Engativá. UPZs with *MI > 0.36* but a lower number of automobiles, surrounded by neighbors with similar characteristics (*High-Low*), are observed in 3 UPZs located in Suba and Teusaquillo.

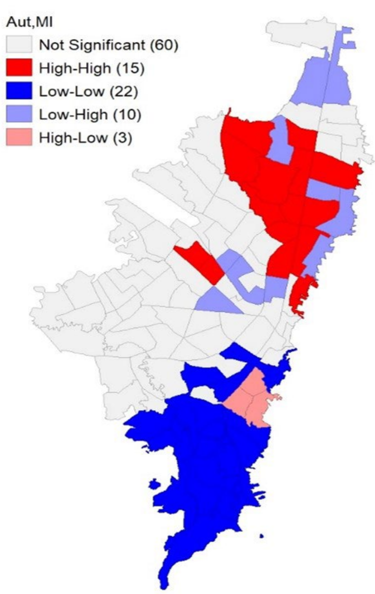


Figure 7. Automobiles with mobility index.

The MI in the High and Very High range is directly related to the number of automobiles and is observed in 10 UPZs distributed across the Suba, Usaquén, and Barrios Unidos districts. Conversely, low MI are associated with low proportions of cars and are found in 10 UPZs located in Usme, Candelaria, Santa Fe and San Cristóbal.

In Figure 8, two relationships concerning infrastructure in the city of Bogota are explored:

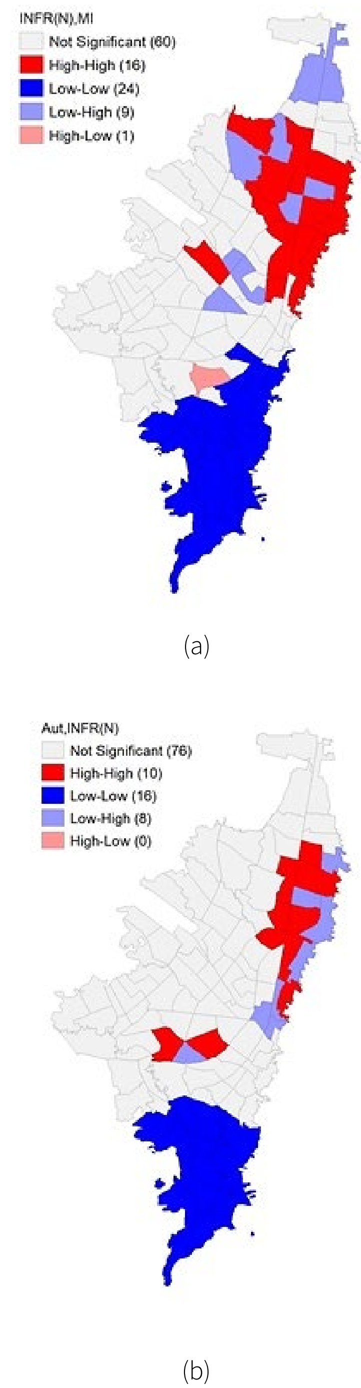


Figure 8. (a) Infrastructure with mobility index and (b) Automobiles with infrastructure

In Figure 8a, focusing on Infrastructure with MI, a positive autocorrelation is observed between maximum infrastructure and a good MI (*MI > 0,36*). This is found in 16 UPZs located in Suba, Usaquén, Chapinero, Teusaquillo, Fontibón and Barrios

Unidos. On the other hand, UPZs with scarce infrastructure also show low MI (*MI < 0,25*) and they are located in 24 UPZs located in Usme, Ciudad Bolívar, Santa Fe, San Cristóbal, Los Mártires, Rafael Uribe and Tunjuelito.

In Figure 8b, concerning Automobiles with Infrastructure, 10 UPZs are observed to have a high proportion of cars while being adjacent to UPZs with maximum infrastructure; these are in Puente Aranda, Usaquén, Chapinero, Suba and Barrios Unidos districts. In contrast, 16 UPZs have a low proportion of cars and are adjacent to areas with scarce infrastructure; these are in Usme, Ciudad Bolívar, San Cristóbal, Rafael Uribe and Tunjuelito.

These results highlight the importance of studying the in infrastructure to improve both the quality of life of the inhabitants and the mobility within the city. Identifying these UPZs allows urban planners and public policy makers to focus their efforts and resources on zones that most urgently require them, aiming for an improvement in mobility and well-being in the city of Bogota D.C.

6. Conclusions

In the initial stage of the study, descriptive analysis has been instrumental in identifying variables most closely correlated with the MI. A clear trend of higher mobility is observed in the localities of Suba and Usaquén, while Usme and Ciudad Bolívar display low indices. The variables that most strongly correlated with the MI include were social stratum, the number of automobiles, the number of motorcycles, and the quantity of public parking spaces.

Interestingly, the UPZs with a high proportion of automobiles tend to have a high MI, particularly in higher socioeconomic strata (4, 5, and 6). This has implications for urban planning and the implementation of electric mobility policies, such as the location of charging stations (electrolineras).

The use of the Moran’s Index for assessing spatial autocorrelation has further characterized the spatial heterogeneity of these variables across the UPZs, revealing that Bogota is divided into zones with specific characteristics of mobility and socioeconomic stratification. This suggests the need for implementing targeted policies and strategies to address these challenges.

Ongoing research on electric mobility will benefit from these findings, particularly for the optimization of charging infrastructure. For this purpose, it will be crucial to consider a variety of factors, such as the number of households, the average number of automobiles and motorcycles in circulation, the presence of universities and shopping centers, and socioeconomic stratification. Spatial autocorrelation techniques could play an essential role in identifying spatial patterns for the optimal location of electric station.

Conflict of interest

The authors have no conflict of interest to declare.

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