ORIGINAL ARTICLE

Socio-environmental factors contributing to the high incidence of COVID-19 in a border city in northern Uruguay
Fatores socioambientais que contribuem para alta incidência de COVID-19 em cidade fronteiriça no norte do Uruguai
Factores socioambientales que contribuyen a alta incidencia de COVID-19 en ciudad fronteriza del norte de Uruguay

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ABSTRACT

Background and Objectives: the present study was conducted in the city of Rivera, situated in northern Uruguay on the border with Brazil. The disease initially progressed slowly in 2020, with subsequent outbreaks followed by a rapid increase in incidence. The objective was to explore the relationship between the spatial distribution of COVID-19 cases in a binational city and variables such as socioeconomic status, population density, and mobility patterns, with the aim of informing public policies. **Methods**: an exploratory study was conducted between August 2020 and January 2021 using data obtained from the Ministry of Health. The explanatory variables considered included population density, socioeconomic level, and mobility. Three distinct periods from 2020 to 2021 were identified. Spatial autocorrelation was analyzed using Moran's Index and the Gi* statistic (Getis & Ord). Hierarchical cluster analysis was employed to identify homogeneous groups of census segments. **Results**: a total of 1,846 cases were georeferenced. Through hierarchical cluster analysis, seven homogeneous groups were identified. Mobility was found to explain the incidence of cases among the high socioeconomic level group, while population density accounted for the differences observed in the low socioeconomic group. **Conclusion**: in this city, priority should be given to populations residing in areas with higher population density and greater mobility. This small-scale territorial analysis provides valuable information for developing localized policies aimed at addressing health crises.

Keywords: *COVID-19. Spatial-temporal Analysis. Social Mobility. Socioeconomic Level. Population Density.*

RESUMO

Justificativa e Objetivos: o presente estudo foi realizado na cidade de Rivera, localizada no norte do Uruguai, na fronteira com o Brasil. A doença progrediu lentamente durante 2020, com surtos subsequentes seguidos por um rápido aumento na incidência. O objetivo foi explorar a relação entre a distribuição espacial dos casos de COVID-19 em uma cidade binacional e variáveis como nível socioeconômico, densidade populacional e padrões de mobilidade, com o objetivo de informar políticas públicas. **Métodos**: estudo exploratório foi realizado entre agosto de 2020 e janeiro de 2021 com dados do Ministério da Saúde. As variáveis explicativas incluíram densidade populacional, nível socioeconômico e mobilidade. Três períodos distintos de 2020 a 2021 foram identificados. Autocorrelação espacial foi analisada com o Índice de Moran e a estatística Gi* (Getis & Ord). Utilizando a análise de *cluster* hierárquico, foi possível identificar grupos homogêneos de segmentos censitários. **Resultados:** um total de 1.846 casos foi georreferenciado. Através da análise de *cluster* hierárquico, sete grupos homogêneos foram identificados. A mobilidade foi encontrada como explicativa para a incidência de casos no grupo de alto nível socioeconômico, enquanto a densidade populacional explicou as diferenças observadas no grupo de baixo nível socioeconômico. **Conclusão**: nessa cidade, as populações a serem priorizadas são aquelas que residem em áreas com maior densidade populacional e maior mobilidade. Essa análise territorial em pequena escala fornece informações valiosas para o desenvolvimento de políticas locais destinadas a lidar com crises de saúde.

Descritores: *Análise Espaço-temporal. Mobilidade Social. Nível Socioeconômico. Densidade Demográfica.*

RESUMEN

Justificación y Objetivos: el estudio se realizó en la ciudad de Rivera, situada en el norte del país en la frontera con Brasil. La enfermedad progresó lentamente durante 2020, con brotes posteriores seguidos de un rápido aumento de la incidencia. El objetivo fue explorar la relación entre la distribución espacial de los casos de COVID-19 en una ciudad binacional y variables como nivel socioeconómico, densidad poblacional y patrones de movilidad, con el objetivo de informar políticas públicas. **Métodos**: se realizó un estudio exploratorio entre agosto 2020 y enero 2021 con datos del Ministerio de Salud, considerando semanas epidemiológicas. Las variables explicativas consideradas fueron densidad poblacional, nivel socioeconómico y movilidad. Se identificaron tres periodos temporales desde agosto 2020 hasta enero 2021. Se analizó la autocorrelación espacial empleando el Índice de Moran y estadística Gi* (Getis & Ord). Mediante el análisis de *cluster* jerárquico, fue posible identificar grupos homogéneos de segmentos censales. **Resultados**: se georreferenciaron un total de 1.846 casos. Mediante análisis de *cluster* jerárquico, se identificaron siete grupos homogéneos. Para el nivel alto socioeconómico, la movilidad es el factor explicativo de una mayor incidencia de casos. Mientras que, para para el grupo de nivel bajo, la densidad de la población fue el factor explicativo de las diferencias en la presentación de la enfermedad. **Conclusión:** la población a ser priorizada en esta ciudad corresponde a aquellas zonas con mayor densidad poblacional y donde se incrementa la movilidad. El análisis territorial a pequeña escala genera información para la construcción de política local, ante una crisis sanitaria, que la hace más eficaz.

Palabras Clave: *Análisis Espacio-temporal. Movilidad Social. Nivel Socioeconómico. Densidad de Población.*

INTRODUCTION

The first COVID-19 cases were detected in Uruguay on March 13, 2020. Multiple measurements indicated a low incidence initially,[1] and any outbreaks that occurred were studied and controlled through non-pharmacological measures. However, a significant increase in the number of cases began in October 2020.

In January 2021, the cumulative incidence and mortality rates in Brazil were 4,118.3 and 101.3 per 100,000 inhabitants, respectively. In Argentina, these rates stood at 4,101.8 and 103.1 per 100,000 inhabitants, while in Paraguay they were 1,771.7 and 36.2 per 100,000, respectively. Uruguay recorded an incidence rate of 1,041.2 and a mortality rate of 10.5 per 100,000 inhabitants.[2] Before the study period (August 2020 to January 2021), the Ministry of Public Health issued its last report on July 28, 2020, which documented 1,218 COVID-19 cases in Uruguay, resulting in an incidence rate of 34.5 per 100,000 inhabitants.[3] As of February 14, 2021, there were 48,909 laboratory-confirmed cases in Uruguay, with a cumulative incidence rate of 1,385.17 cases per 100,000 inhabitants.[4]

Considering the significant increase in cases between August 2020 and January 2021, this time frame was chosen as the study period for this research.

Rivera, located in northern Uruguay, shares a permeable border with the city of Santana do Livramento, Brazil. The border is traversed by a single street, posing challenges for effective control measures. The majority of the population has dual citizenship, and many workers provide services on both sides of the border, including health care workers. This region has garnered consistent attention due to the high volume of people freely moving across the border, which increases the risk of introducing new variants.

The association between SARS-CoV-2 and public transport has been recognized as important;[5,6,7] however, the Uruguayan and Brazilian sides of the city of Rivera do not share transportation. Nevertheless, Rivera has witnessed a proliferation of tax-free stores known as free shops, which serve as a significant driver for the local economy, creating employment opportunities and facilitating a continuous flow of people crossing the border. The commercial area is situated in the city center and in close proximity to the street that connects this binational city.

In October 2020, Rivera, a department in Uruguay, recorded the highest cumulative incidence of COVID-19 cases in the entire country, higher than all other departments, including the capital city of Montevideo.[8] Joint actions were taken by health authorities on both sides of the border to diagnose COVID-19, follow up on detected cases, exchange epidemiological information, and adopt measures for travelers, among others.[9] The vaccination program in Uruguay commenced in March 2021, initially targeting specific priority groups. It is important to consider the socioeconomic disparities within the population of Rivera as this can influence the characterization of the epidemiological situation.[10] Population density is another crucial factor to be considered.[11] Higher population density is typically associated with increased incidence and is often linked to more densely populated areas.[12]

Certain models have suggested that maintaining physical distance may not significantly contribute to disease transmission.[13] However, this study considers mobility as an important variable in analyzing disease transmission. It is worth noting that some authors argue that measures restricting mobility have not effectively prevented the progression of the pandemic.[14] Some authors have approached mobility differently by utilizing categories provided by the data provider (https://www.google.com/covid19/mobility/?hl=es). These categories take into account various levels of mobility, such as being in a park or a residential unit, as opposed to being in workplaces, stores, pharmacies, or using public transportation. Conversely, other studies treated all mobility categories equally in their analyses.[15]

It is necessary to understand the structural elements within spaces that can help explain the problem under study.[16] Consequently, the distribution of the subject under study is analyzed by considering demographic, environmental, and socioeconomic variables of the population. Moreover, the behavior of the subject in space is examined to draw meaningful conclusions. The present study examined the pre-existing structural conditions within the city that are likely to account for the fluctuations in the number of COVID-19 cases.

The objective was to explore the relationship between the spatial distribution of COVID-19 cases in a binational city and variables such as socioeconomic status, population density, and mobility patterns, with the aim of informing public policies.

METHODS

The city of Rivera, located at the coordinates 55° 33'3"W; 30° 54'19"S, is part of a conurbation space along with the city of Santana do Livramento Brazil, where 155,221 people reside in a binational city with a dry border. Rivera has a population of 78,900 (ine.gub.uy), 53% of which are women. In total, 11.7% of households fall below the poverty line, 49.6% are not connected to the general sanitation network and 8.9% are not connected to the drinking water distribution network. Those who are 25 years of age and older have an average of 8.1 years of education, the lowest in Uruguay. Labor market indicators show the activity rate (55.2%) and employment rate (50.4%) to be below the national average, and the percentage of informal work is among the highest, with 42% of employed persons not contributing to social security.[17]

The present study was conducted in this city, located in northern Uruguay, focusing on the period when the cases were on the rise. It shares a border with Brazil, which adds complexity to the analysis of the problem to be addressed. This research includes an analysis of the socio-environmental variables that may have contributed to the transmission of the virus.
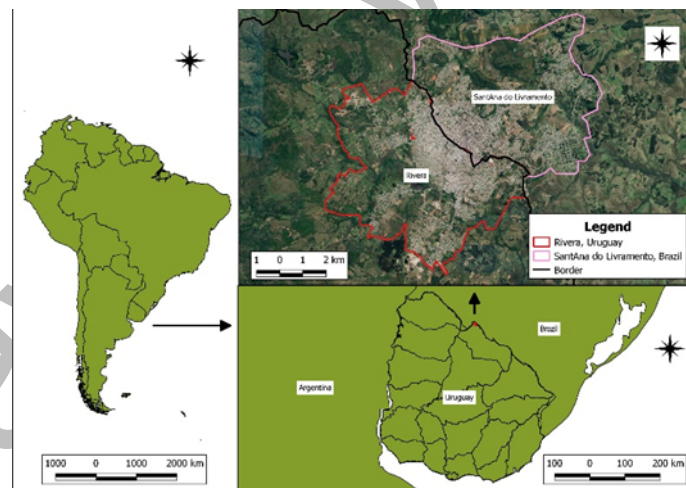

Figure 1. The city of Rivera, Uruguay

This is an exploratory study. The data of COVID-19 cases were obtained from the Ministry of Health's surveillance system (https://www.gub.uy/ministerio-salud-publica/home), incorporating incident cases within the census segment from August 2020 to January 2021. Throughout this timeframe, a cumulative total of 2,277 COVID-19 cases were reported.

By conducting a detailed analysis of the cases that were reported, it was found that some of them were outside the study area, many of which were in the neighboring

city of Santana do Livramento, Brazil. After this analysis, 1,846 cases were included, which are presented according to epidemiological week (Figure 2).
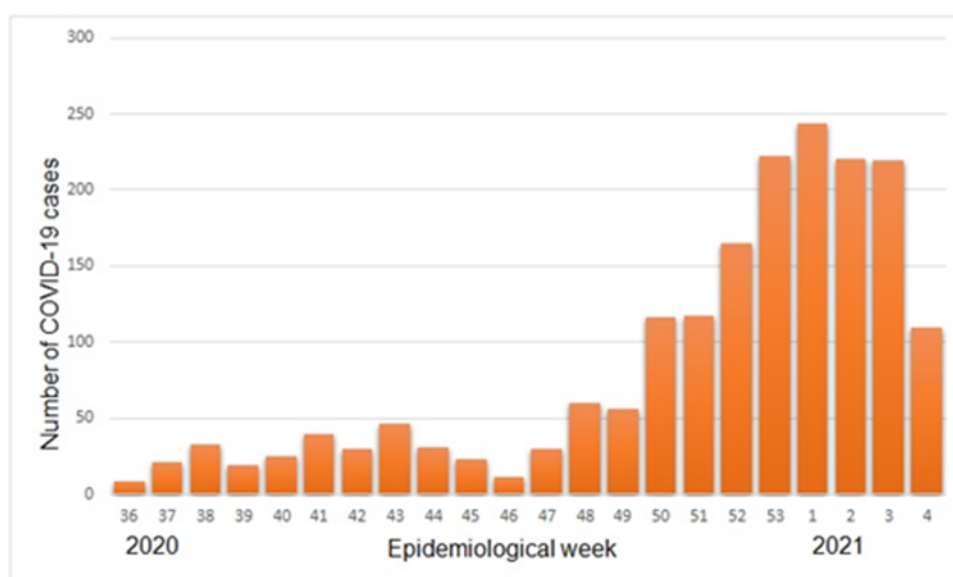

Figure 2. COVID 19 cases in the city of Rivera, Uruguay, according to epidemiological week, 2020-2021

In terms of temporality, the data were distributed according to epidemiological weeks (22 in total), and with regard to spatial data, the census segment (administrative unit) was used (59 segments for the city of Rivera). The population density per segment was calculated in real values expressed in inhabitants per square kilometer, based on data from the 2011 census (www.ine.gub.uy). They are sorted according to their standard deviation in relation to mean.

A socioeconomic status indicator was computed for each administrative unit, defined as census segments, using data sourced from the 2011 census conducted by the Uruguayan National Statistics Institute (www.ine.gub.uy). The variables considered encompassed housing conditions, wall material, primary roof material, drinking water supply, persons per bedroom, waste disposal system, energy source for cooking, household internet access, unmet basic needs (three or more), ethnicity, education, basic formal educational level, and social security income.[18]

The construction of this socioeconomic indicator involved employing principal factor analysis,[10] utilizing Stata version 11 for statistical analysis. The first factor explained 73.5% of the variance in the original variables within the model. Following this, the distribution of this factor was divided into quartiles to depict socioeconomic levels.

The formula utilized for computing the socioeconomic indicator is delineated as follows:

$$\gamma_{ij} = \sum_{k=1}^{q} z_{ik} b_{kj} + e_{ij} \qquad \text{[Harman, 1976)}$$

Where
y_{ij} is the ith observation of the jth variable;
z_{ik} is the ith observation of the kth of the common factor;
b_{kj} is factor loading;
e_{ij} is a unique factor of the jth's variable.

Mobility data were obtained from smartphones and handle devices (https://www.google.com/covid19/mobility/?hl=es) that agreed to provide location data. They were classified by location according to the following categories: retail and recreation; parks; grocery stores and pharmacies; workplaces; transport "transit" hubs; and residential areas.[15] Each value was compared to a baseline value (five weeks, from January 3 to February 6, 2020), and the data used was the percentage change[15] relative to that baseline value. The reference value was the median. In the study for each census segment, mean mobility was weighted according to the number of cases during each epidemiological week.

The temporal behavior of cases presented three periods in 2020 and 2021: period one was stable, from weeks 36 to 46; period two had rapid growth from weeks 47 to one; and period three was stable and declining from weeks two to four (Figure 2).

The number of cases and mobility was grouped according to those three periods, which resulted in eight variables, namely: the number of cases per segment during periods one, two, and three; mobility, weighted by the number of cases in each segment during periods one, two and three; and population density (inhabitants/km^2) and socioeconomic level for each segment. The eight variables that were used throughout the analysis were thereby defined.

The behavior of the pandemic in a medium-sized city was explored based on census segments,[16] which represented administrative divisions that were roughly equal to neighborhoods. By using these segments, it was possible to identify variations in conditions related to positive cases as well as variables that characterized the population. In this regard, local differences within a medium-sized city could be represented. So as not to assume a spatial correlation among the variables, which would be expected from a homogeneous medium-sized city, autocorrelation was assessed using Moran's Index.[19] The Gi*statistic was used to identify the degree of spatial correlation for each variable in

each segment. A matrix was built that included the census segments and the distribution of the variables in those segments.

The relationships among the variables were detected using a regression tree hierarchical cluster analysis, with the standardized values of the local Gi* statistic for each variable. It was thereby possible to identify groups of segments in which the values of the variable behaved similarly. These clusters were spatialized in a geographic information system to analyze the spatial patterns of the distribution of COVID-19 cases to contribute to possible explanations for this behavior.

All of the data were geocoded with a geographic information system using ArcGIS$^{©}$ 10.4. To assess the spatial autocorrelation of the variables, Moran's global spatial autocorrelation index (Moran's I) was used as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad \text{[Moran, 1948)}$$

Where
z_i is the deviation of an attribute for feature *i from its mean* $(x_i - \bar{X})$;
$\omega_{i,j}$ is the spatial weight between features *i* and *j*;
S_0 is the aggregate of all the spatial weights.

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{i,j} z_i z_j$$

A positive spatial autocorrelation was identified for each of the eight variables. The general Gi* statistic (Getis & Ord) was then used, with census segments as the spatial unit. The general Gi* statistic is a global method to quantify the degree of spatial autocorrelation of each variable. It measures how autocorrelation varies locally in the study area and calculates a value for each geographic entity (census segment).

The local mean for an entity and its neighbors is proportionally compared to the mean for the whole set. A matrix of weights is used to calculate the local mean, which is a function of the distance (*d*) between the point considered and its neighbors. This matrix, $\omega_{ij}(d)$, takes values of 0 for distant points and 1 for points with a distance less than *d*.

The Getis-Ord Gi statistic* (Getis-Ord, 1992) was computed as follows:

$$G_i^*(d) = \frac{\sum_{j=1}^{n} \omega_{ij}(d).x_j}{\sum_{j=1}^{n} x_j} \qquad \text{(Ord \& Getis, 1995)}$$

A matrix was constructed with standardized values, and based on this matrix, a hierarchical cluster analysis was performed for the three periods as a whole. This made it possible to use the aggregation method to detect groups that behaved homogeneously

concerning the segment, which resulted in those with the smallest distances in the matrix being grouped. The Euclidean distance to the centroids was measured, which is a method that detects the point at which there is a sharp jump in the distance coefficient. Based on this point, seven homogeneous groups of behavior were identified (Table 1) using SPSS version 23.

For each of the eight variables, a qualitative assessment was performed according to how close or far it was from the mean: very high - above 1 standard deviation; high - between 0 and 1 standard deviation; low - between 0 and -1 standard deviation; and very low - below -1 standard deviation.

Ethical considerations: as previously indicated, secondary data provided by the Ministry of Health (www.gub.uy/ministerio-salud-publica/) were used in the study, considering the study's temporal period and the locality from which the cases originated. However, these data did not allow for individual identification.

RESULTS

In the city, the distribution of the eight variables, as clarified in the methodology, is categorized into very low, low, high, and very high, as depicted in Figure 3. The graphs showcased in the figure illustrate the breakdown of case and mobility variables across periods one, two, and three. Additionally, data on population density and socioeconomic index variables are included.
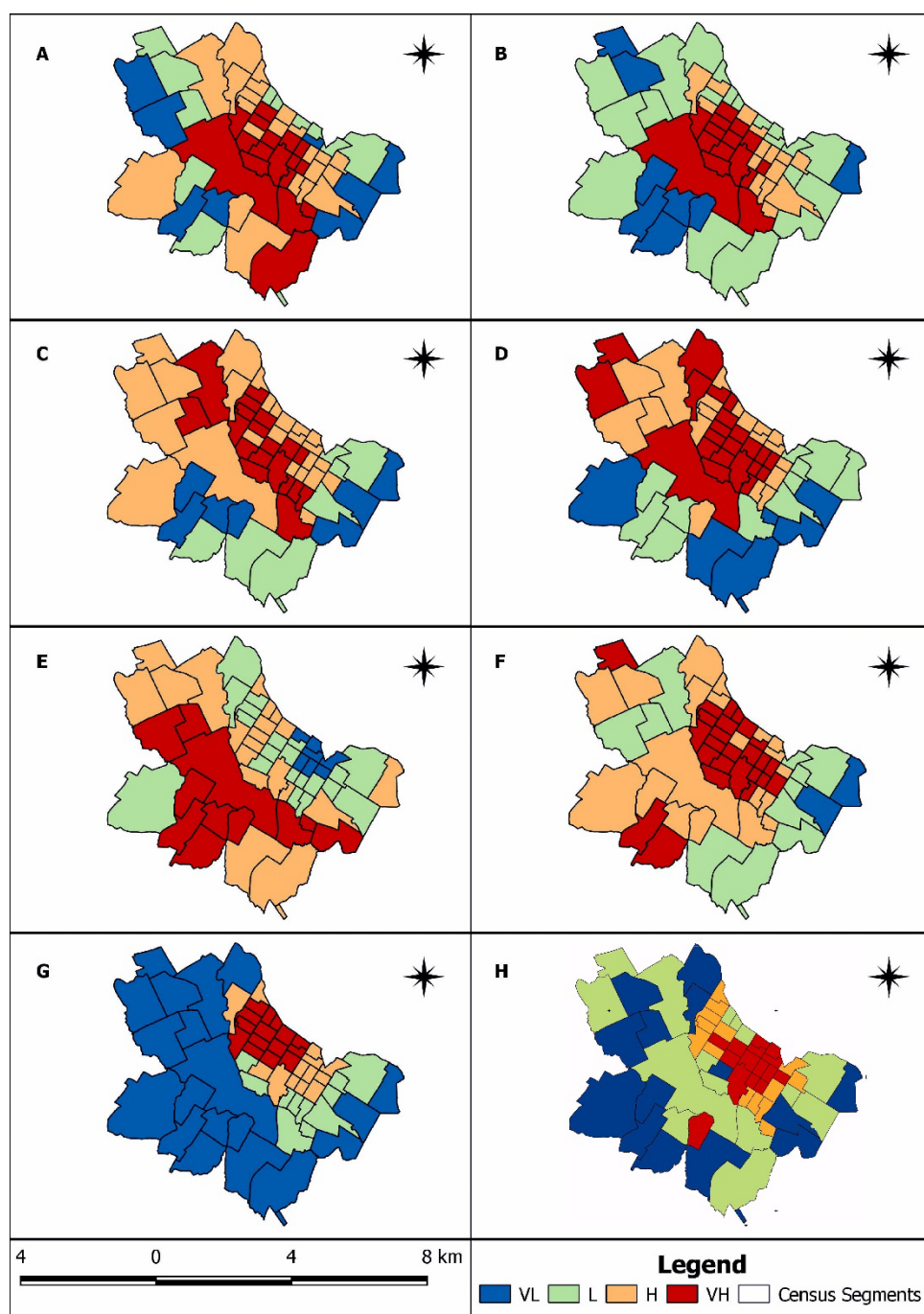
Figure 3. Variables in Rivera based on the categories generated
Legend: (a) distribution of cases in period one; (b) distribution of cases in period two; (c) distribution of cases in period three; (d) mobility in period one; (e) mobility in period two; (f) mobility in period three; (g) population density; (h) socioeconomic index.

Throughout the three periods, it was observed that the highest number of reported COVID-19 cases occurred in the central segments. The same pattern was observed for population density. While mobility predominated in the central segments during periods one and three, it was different in period two, where it was higher in the city's periphery. Finally, the highest socioeconomic level was observed in the central segments near the border with Santana do Livramento (Figure 3).

The result of hierarchical cluster analysis is presented, in which seven clusters are observed (Figure 4). It is essential to analyze this figure and Table 1 together, as the table provides insight into the different variables and their distribution.
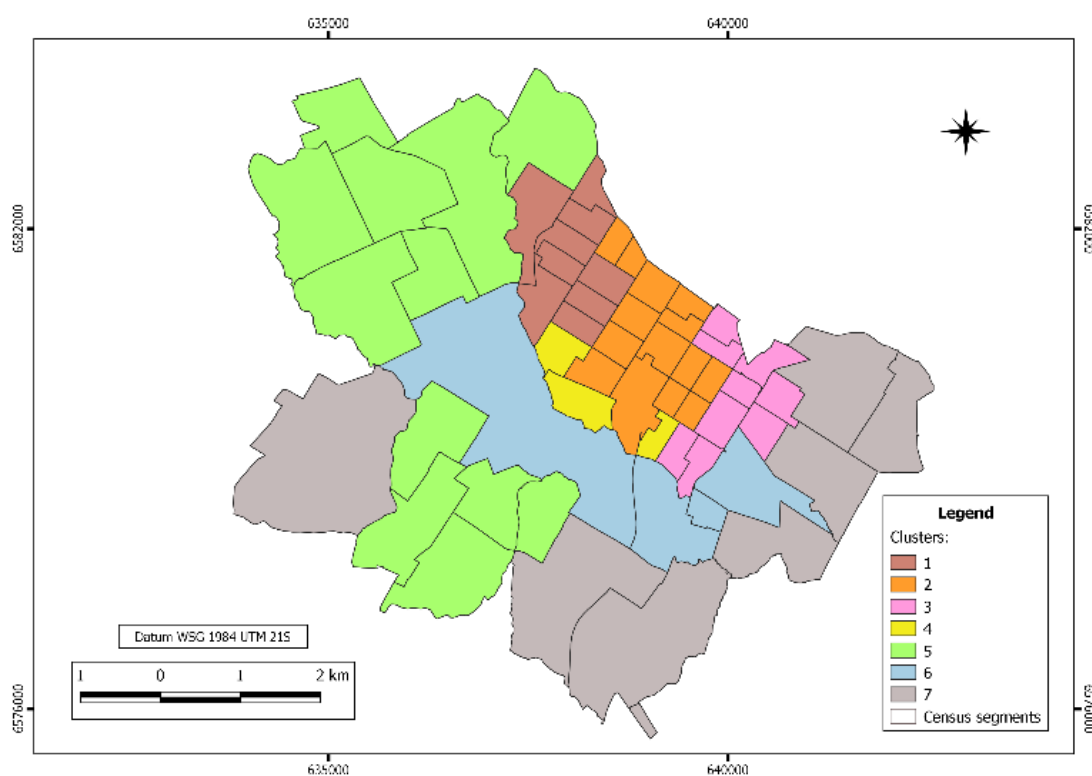

Figure 4. Homogeneous groups in hierarchical analysis of census segments, city of Rivera, Uruguay

The behavior in each cluster was identified for each of the eight variables. Table 1 illustrates the study's eight descriptive variables, along with their respective spatial clustering combinations. Each descriptive variable is classified into one of four levels, very low, low, high, or very high, as described in Table 1. These categories can be seen in greater detail in Table 1, which outlines the classification of each variable in the seven groups.

Table 1. Variables categorized based on homogeneous group, city of Rivera, Uruguay

Variables	Clusters*						
	1	2	3	4	5	6	7
Distribution of cases in period one	H	H	L	VH	L	H	L
Distribution of cases in period two	H	H	H	VH	VL	H	L
Distribution of cases in period three	H	H	L	H	L	H	VL
Mobility in period one	H	H	L	H	L	L	VL
Mobility in period two	L	VL	VL	L	H	H	L
Mobility in period three	H	H	L	VH	L	L	VL
Population density	H	VH	VH	H	VL	L	VL
Socioeconomic index	VH	VH	H	L	VL	L	L
Total cases	**282**	**386**	**275**	**31**	**268**	**195**	**409**

Legend: *VH - very high, H – high, L – low, VL - very low.

Two major clusters can be seen from these results. One consists of cluster segments one, two and three, which represent areas with high and very high purchasing

power and high and very high population density. We call this clustering the high level. The other group contains the segments in clusters five, six and seven, representing areas with low and very low purchasing power and low and very low population density. We call this clustering the low level.

The high level did not present a uniform evolution over the period analyzed. While clusters one and two always had a high number of cases, the number of cases in cluster three started low, continued high and ended low. The explanatory factor for this difference is mobility. Clusters one and two continued to have high and very high mobility, while cluster three had low and very low mobility.

As for the low level group, while contagion in clusters five and seven remained low and very low, cluster six had a consistently high level of contagion. Here a clear pattern of mobility is not observed, since mobility in clusters five and six are identical. What can be observed is that cluster six displays a lower population density compared to clusters five and seven, where a very low population density can be seen. Within the lower level group, a reduced population density contributes to comparatively fewer reported cases.

DISCUSSION

The distribution of groups in different spaces is influenced by social, cultural, and environmental factors, which manifest in how people utilize these spaces. The variables selected by the study herein made it possible to represent, in part, this expression and to explain differences in how the disease behaved in areas that had greater and fewer number of cases. The territorial level of analysis was based on the greatest degree of detail available, namely, the administrative units (census segments). Local homogeneity in behavior was found when clustering the census segments.

In areas characterized by a high socioeconomic level, mobility appeared to be the key variable in explaining the differences in case numbers. These areas were primarily located in the downtown commercial region closest to the border street connecting Rivera and the city of Santana do Livramento, Brazil. These clusters, labeled as one and two, represented areas that were susceptible to the introduction of new variants due to the significant interdependence between residents on both sides of the border.[20] This is particularly relevant for border cities, where interactions and exchanges between neighboring populations play a substantial role.[20, 21]

However, for areas with a low socioeconomic level, it was observed that clusters with the fewest number of cases (clusters five and seven) exhibited very low population density. Interestingly, even when there was increased mobility during certain periods, the number of cases remained low in these areas. This finding could be attributed to a very low population density

Meanwhile, a greater presence of cases was found in the most densely populated areas of Rivera where there was daily migration associated with a porous border.[21] While it has not been physically possible to completely close this border, authors[22] also point out that such a closure could lead to the use of alternative routes of entry, which would result in a greater risk to the population. Another study of a binational border[23], where there was daily migration of agricultural workers, found that health care could be received on both sides of the border.

The higher incidence of cases in more densely populated areas is consistent with previous research highlighting the association between population density and the spread of the disease.[11, 12, 24, 25] This study emphasizes the importance of considering population density as a significant factor for areas with a low socioeconomic level. Previous studies have also indicated the relevance of socioeconomic level in relation to the number of cases.[16, 26] However, it should be noted that the relationship between the behavior of the number of cases and socioeconomic level is not uniformly consistent.[11,24] Higher indicators in areas with a higher socioeconomic level can sometimes be attributed to better detection[24] of capabilities and individuals' ability to practice isolation, resulting in lower indicators.[27]

While socioeconomic level should be considered, it is essential to also consider factors such as density and mobility when predicting indicators.

In the present study, clusters one and two exhibited high mobility, particularly during the initial weeks. Contrary to some claims that restricting mobility has limited effectiveness in reducing the number of cases,[15, 22] this exploratory study found a positive association between increased mobility and incidence of cases.[28]

The geo-statistical analysis presented herein is considered to be a strength of this work, given that conventional models have been known to be biased because they produce averages without considering geographic variability.[27] Working at the greatest level of

detail possible, as done in this study, allows for identifying specific spatial patterns, and is especially important when analyzing border-specific phenomena.[24] Another strength of this work is that it used socioeconomic information that was analyzed at the level of the census segment.[12]

Furthermore, a study that used a broad scoping review (n=95) argued that most of the research presents data at the district/county level, unlike the study presented herein, which uses microdata. Therefore, this can be considered a better proxy for individual situations.[28]

However, there are limitations to consider. Mobility data did not differentiate statistically between the "residence" category and other categories. Some authors argue that different events occurring in residential areas can result in close proximity among individuals and should not receive distinct treatment.[13] Additionally, mobility data only represent individuals who agreed to provide such information and used the Android system.[29]

As an exploratory study based on secondary data, causality and temporality cannot be determined.[30] Therefore, further research is needed to analyze the social-environmental heterogeneity and mobility within cities, incorporating other environmental variables such as the presence of green space.[31]

Based on the results, it is concluded that priority should be given to areas in the city of Rivera with higher population density and greater mobility. These findings can inform the community in controlling the disease, guide the design of effective public policies, and allocate resources based on scientifically grounded priority criteria, thereby improving effectiveness.[32] Furthermore, given the recognition of the importance of the migration condition, the surveillance system should include socio-environmental variables that also consider the migration condition as a variable to be studied.[33]

To prepare the system for future epidemic situations, health system inequities should also be addressed. This would improve community resilience[34] and deepen ties among binational policies.

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Authors' contributions

Marcel Achkar, conception and design of the work, collection/obtaining results, data analysis and interpretation, drafting the manuscript, critical review of the manuscript, approval of the final version. **Mariana Gómez-Camponovo**, conception and design of the work, collection/obtaining results, data analysis and interpretation, drafting the manuscript, critical review of the manuscript, approval of the final version. **Nicolas Pérez**, conception and design of the work, data analysis and interpretation, drafting the manuscript, critical review of the manuscript, approval of the final version. **Eleuterio Umpiérrez**. conception and design of the work, data analysis and interpretation, critical review of the manuscript, approval of the final version.

The final version of this publication has been approved by all authors, who bear full responsibility for the entirety of the work, including ensuring its accuracy and integrity.