Vulnerability to COVID-19: cluster analysis of census tracts in Malaga, Spain

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The United Nations 2030 Agenda recognized the importance of focusing on cities to achieve sustainable development goals. The COVID 19 pandemic reaffirmed the need to consider spatial variables when analyzing the impact of a risk or an epidemic. Many studies have assessed the impact of this pandemic on countries and its connection with numerous population-related factors, such as vulnerability and resilience. However, there have been less spatial analyses at an urban scale also considering time as a variable. In spite that, some researchers have recently shown how the patterns of the pandemic evolution is changing in time. We performed a case study in Malaga (Spain) using a tempo-spatial analysis with the purpose of going as deep as possible into the micro-scale of the pandemic impacts, without leaving anyone behind. The micro-level research using composite indexes and cluster analysis clarify the living conditions of people. The results show some patterns ~~a~~ of the spatial segregation in the neighborhoods that could oriented better integrated policies and good governance in the recovery process.

Keywords: word; COVID-19; vulnerability; spatial segregation; clusters; 2030 Agenda

1. Introduction

The United Nations 2030 Agenda proposed a roadmap for achieving sustainable development at the country level but emphasized the need to focus on specific objectives and goals at the local level. Cities have become key agents to achieve the required environmental, economic, digital, and social transitions. Numerous authors have integrated the spatial (territorial) scale as the fifth dimension of sustainable development (Sharifi and Yamagata, 2017). The implementation of the 2030 Agenda in cities requires establishing interconnected objectives and goals, with coordinating action plans and tools, based in multi-actors and multilevel urban governance (Castillo and

Haarich, 2013). The literature refers to this as integrated sustainable urban development (UNSSC, 2017). This approach has inspired the urban policies of the United Nations and the European Union (Risi et al., 2020), but cities are still developing practical analyses tools and community mobilization to implement this kind of interdisciplinary perspective (Franch- Pardo et al, 2020).

The global COVID-19 pandemic has emphasized the importance of spatial analyses, especially at the levels of the neighborhood and street, as a useful tool to make a rapid diagnosis and identify the right population. This approach ~~can help~~ has helped locate the most vulnerable groups, attend to their needs, and increase their resilience in the face of risks or disasters (Mishra et al, 2020).

Several researches show how the spread dynamic is being regionalized and highly depending on the population density (Bourdin et al., 2021; Franch-Pardo et al., 2020; Wang et al., 2020), because, although the initial hot spots were located in areas with good communications and higher demographic density, the evolution of the pandemic spread to less populated areas. These researches insist in the need to analyze the spatial dynamic of the pandemic and its relation to territorial, social and healthcare factors, as it already happened with other epidemics and similar situations (Lall &Wahba, 2020; Lai et al., 2009; Pfeiffer et al., 2008; Sajadi et al., 2020; Adecunle et al, 2020; Mollalo et al., 2020; Xie et al., 2020; Gross et al., 2020). This means that to understand the complexity of these territorial processes, with multiple factors involved, it is necessary to use multidimensional statistical tools, as shown for example in Anselin, 1995; Cordes & Castro, 2020; Coccia, M, 2020; Labib et al., 2020; Desjardins et al., 2020 or Johnson et al, 221. With this baseline, and with the proposals of De Caprio et al., (2020), we have analyzed the relation of the territorial vulnerability and the pandemic spread.

So, the present research aims to address urban vulnerability at the micro-scale and how this affects to the COVID-19 spread, by analysing the impact of the epidemic waves ~~of COVID-19~~ on different neighborhoods and determining the link between population vulnerability and level of ~~disease~~ contagion (Maroko et al, 2020). We propose to use the tempo-spatial analysis at census tracks level with clustering methods to understand better the relations between the spread of the disease and the socio-economic preconditions of each neighborhood.

We focused on Malaga, a city in southern Spain with a population of about 500,000. Malaga has a database with geo-referenced information at the scale of the census ~~section~~ tracts. This includes composite indicators that measure the different dimensions of urban vulnerability. Previous research analyzed data from the first four waves of COVID-19 (Bárcena- Martín et al., 2021). Cross-referencing of information can provide identification of the most vulnerable groups, and the reasons they live where they do. We believe that this type of analysis provides an important basis for guiding the design of integrated policies and governance systems that can help achieve the goals of the 2030 Agenda (Flood et al, 2021). For example, Madrid (Spain) has used the spatial analysis and the cluster method to identify some patterns in the procedures and calls to social services in the census tracts, during and after the COVID lockdown. With this information they have improved the personal attention to the vulnerable families, which is one of the targets of the Goal 10 “Reduced inequalities” of the 2030 Agenda.

2. Literature review.

Stiglitz et al. (2020) concluded that pandemics rarely affect an entire population evenly. For example, although the Black Death of the 14th century reduced the world's overall population by about one-third, the greatest number of deaths were in the poorest populations. Medieval Europe was densely populated by undernourished and overworked peasants, and this facilitated the spread and death from bubonic plague. In modern times, outbreaks of Ebola were also linked to rural and remote areas of equatorial Africa (World Health Organization, 2015). Because poorer populations have higher prevalence~~s~~ of chronic diseases (such as heart disease, diabetes, cancer, chronic obstructive pulmonary disease, chronic kidney disease, and obesity), they also have a higher risk of mortality from COVID-19 (Hacker et al., 2021; Fekadu et al., 2021). These crises caused shock waves in society, because they expanded existing vulnerabilities and led to multiple harmful effects, most notably death, disease, and adverse economic and social repercussions related to control measures.

Multiple studies have examined the impact of COVID-19 in different countries (Karaye and Horney, 2020; Macharia et al, 2020) and on the most vulnerable groups. ~~However, fewer~~ Some studies have examined its impact at the level of cities and neighborhoods and its possible exacerbation of social inequalities (Lee and Ramirez, 2021; Fu and Zhai, 2021; Krellenberg and Koch, 2021; Kayanan et al., 2020).

At the early stages of the pandemic, Karaye and Horney (2020) examined the association between the number of cases of COVID-19 and social vulnerability in the United States, and identified counties with the greatest vulnerability based on a social vulnerability index (SVI). Their results showed that, in these first months of the pandemic, minority status, language, household composition, mode of transportation, size and conditions of housing, type and number of jobs, and disability were associated with increased risk of COVID-19. Their results also indicated that the relationship between social vulnerability and COVID-19 varied among counties. In particular, the variables most associated with higher numbers of cases were not the same in southwest

Georgia (household composition and disability) as in New York City (minority status and language). But the main finding of this study is that more socially vulnerable counties in the U.S. had more cases of COVID-19. They demonstrated to be valid only for the first months of the pandemic, as shown for example in Lee and Ramirez (2021). This study reveals that socioeconomic links are not always clear and depend on certain variables that may vary by scale and time. In fact, the relationship between COVID and social vulnerability varied from strong to moderate and weaker over the first year. In any case, both studies underscore the importance of including time as a variable to analyze the evolution of the pandemic, as patterns and relations are shown to be variable in time.

Consistent with these findings, Dasgupta et al. (2020) also showed that the most socially vulnerable counties, particularly those with higher percentages of racial and ethnic minority residents, high-density housing structures, and crowded housing units, had greater risk of becoming a COVID-19 "hotspots", especially in less urban areas. Within the counties that had these hotspots, the specific areas with the greatest social vulnerabilities had significantly higher incidences of COVID-19. The same focus was used by Sharoda et al. (2020) in United State.

The CORDIS Programme of European Commission conducted an analysis to study the spatial impact in the European countries. They concluded that in the UK the pandemic had a wider spread than the rest of Europe, due probably to a late lockdown. The region of Helsinki accumulated the 69% of the confirmed cases in Finland, the Portuguese North Region (around Porto) concentrated the 60% of the cases in Portugal and the Oslo region concentrated the 58% of the cases in Norway. But, having the city of London more cases than any other area of UK, it supposed less than 17% of the cases in UK (European Commission, 2021). They remarked that the initial foci are usually in well-connected regions with higher affluence, but, as an outbreak spreads, the areas with less affluence are the most affected. Therefore, they suggested the importance of the spatial studies to dig in the raisons of the spread.

In this sense, Buffalo & Rydzewski (2021) analyzed the spatial dynamics of the COVID-19 pandemic in the province of Cordoba (Argentina). Their results indicated that the spread of COVID-19 at the regional level was most common around corridors defined by the road network, with the greatest circulation at the level of the province and within the province of Córdoba, and was related to flows and existing links between localities and the urban hierarchy. They concluded that the dynamics at the intra-urban and inter-urban scales reflects spatial mobility and the functional links of the population within a region.

To investigate the pre-existing reasons that spread the pandemic from the areas with the greatest population flow to the worst communicated, authors such as Rodríguez-Pose and Burlina (2021) studied the COVID-19 pandemic in 206 regions of 23 European countries, and focused on the uneven geography of COVID-19-related mortality during the first wave of the pandemic. They found the greatest number of deaths were in 16 of these 206 regions. Regions that were highly connected, with colder and drier climates, with high levels of air pollution, and with poorly equipped health systems had the greatest death rates. Institutional factors also played an important role.

This same pattern was reported in the United Kingdom. In particular, people who lived in areas with fewer economic resources were twice as likely to die from COVID-19 as those who lived in areas with more resources; blacks were three to four times more likely to die than whites; and men with low-skill jobs were four times more likely to die than professionals. Thus, as Whitehead et al. (2020) point out, we are not "all in this together", because the underprivileged people in society are suffering the most. Although a virus is the cause of the pandemic, the inequalities it generates have social causes, and only through the "organized efforts of society" can they be prevented.

The Spanish cities of Madrid, Barcelona, Valencia and Málaga have developed spatial studies to understand the contagious of the virus and most of them have concluded the importance of the socio economic, environmental and cultural previous conditions of the population (Ayuntamiento de Madrid, 2020; Marí-Dell'Olmo et al., 2021; García et al., 2021; Bárcena-Martín et al., 2022).

The studies of the COVID spread in Málaga, such as Miramontes et al. (2021) showed that the pandemic has given a new perspective to spatial approaches for examination of risk and importance of place and time. The spatial and temporal analysis of the COVID-19 pandemic has been fundamental in helping to reduce mortality, and is very important for crisis management. Research on the causes of the different risks in different populations is therefore important. An analysis of the spatial distribution of cases and the presence of patterns and trends must be accompanied by an analysis of population flows and movements; clinical, social, and epidemiological vulnerabilities; and socioeconomic repercussions. Hence, the correlation between the distribution of COVID-19 and various factors related to the natural environment and the human environment must be examined at multiple scales. This is the approach of the present research.

3. Materials and methods

3.1 Case study

This case study was performed in the city of Malaga and its 434 spatial census tracts (CT). Malaga is located in southern Spain and it has more than 570,000 inhabitants in a metropolis of almost 1 million (the sixth urban area in Spain). Malaga has an urban pattern typical of European Mediterranean cities, in that it is compact and complex. Diverse cultures have passed through this region since 3000 years ago, as the ancient Phoenician, Roman or Arab civilizations, and these have had a great influence on the natural ecosystem. Malaga's economy is based on urban cultural tourism and the construction sector, although technological and logistical services are also important and is surrounded by agricultural regions that underlie its characteristic food culture.

The historical evolution of this millenarian city has generated a certain social and spatial segregation, in which individuals in a few areas have very good living conditions and high quality of life, and many more live in neighborhoods that are highly vulnerable. According to the Statistical National Institute, Andalusia is the Spanish region with the highest risk of poverty and the second with the worst level of average income per household. Malaga is the second Andalusian city with the largest number of inhabitants and the supposed economic capital of Andalusia, but the differences between the population are very severe, as shown in (Bárcena- Martín et al., 2021). For example, there's a neighborhood in Málaga among de 1,6% richest of Spain and a neighborhood in Málaga among the 99,9% poorest of Spain. Figure 1 is showing the distribution of the vulnerability in Málaga, classified in four quartiles, from the lowest vulnerability (Q1) to the highest (Q4),

The arrival of COVID-19 offered the opportunity to study if these previous unbalanced conditions could increase the spatial and social inequities, as occurred during other pandemics throughout history, because living conditions affect the resilience of individuals and areas to diseases. Our research took advantage of other studies (mentioned in the next section) to analyze the available spatiotemporal data and determine the links between the mortality rates of COVID and these geographical patterns.

3.2. Materials

To measure the vulnerability of the different neighborhoods of Malaga, we used a composite index developed in 2021 by the CIEDES Foundation, in collaboration with the Malaga City Council and the University of Malaga, described and detailed in Bárcena- Martín et al, (2021)

In this work, the level of vulnerability of each census tract was measured trough a multidimensional vulnerability index composed by 19 variables arranged in 4 dimensions: socioeconomic, demographic, social care (needs of the people who inhabit the space), and territorial (quality of the space they occupy) (see **Figure 2**). The selection of variables mostly coincided with those used by other studies and authors for vulnerability analysis in other cities in Spain (Egea Jiménez et al., 2008; Ayuntamiento de Madrid, 2018).

We built a database with more than 200 originally data, collected from official sources, and the information of a short-term survey on living conditions that we conducted. The initial problem arising was that these variables were obtained from many different sources, from the Municipal Register of Inhabitants, the National Institute of Statistics, the Survey of Living Conditions (ECV) of the National Institute of Statistics, the Information System for Users of Social Services or the Malaga Urban Environment Observatory, etc. Most of them were using heterogenic spatial units, ranging from postal codes, districts, classical neighborhoods, etc. To overcome this drawback, all the variables were translated into the minimal spatial unit, the census tract (CT), using a cartographical algorithm, specifically designed for the city of Málaga, able to transform all the information into the same (minimal) units. This algorithm was using the cartographical information on the frontier of the different spatial units, as well as the Municipal Register of Inhabitants, that contains the exact address of each inhabitant in the city. The CT is smaller than the municipality and has easily identifiable limits, such as natural terrain features, permanent buildings, and roads. Each CT has a population of about 1000 to 2500 inhabitants.

Once all the variables were referenced to the same spatial units, a normalization process was applied so that all of them were ranged in [0,1], being in all the cases 0 the best situation and 1 the worst. Therefore, all the variables were normalized so that in any variable, despite being a maximizing or minimizing one, a higher value means a worse situation in that characteristic. Finally, the normalized variables were grouped in four categories, demographic, socioeconomic, social care, and territorial, and a linear weighted aggregation was conducted to obtain a final vulnerability index. Following Stapleton and Garrod (2007), we chose to give the same weight to the dimensions and distribute the weights proportionally within each dimension. Note that this dimension's aggregation method allows compensation between them. This is, authors assume that, for example, a low score in the level of income can be compensated (according to the assigned weights) by an increase in the level of education and this compensation is constant.

About the COVID-19 data, the Andalusian Health Service provided ~~has data on~~ the total number of confirmed COVID-19 infections in Malaga daily for each census tract for the whole period between March 5, 2020 to March 31, 2021, covering the first four waves of the pandemic (**Figure 3**).

With this data, we computed for each CT the numbers of accumulated cases by 1,000 inhabitants over the previous 14 days period. The date limits for each wave were fixed according to the main local minimum of the curve of the evolution of the pandemic in **Figure 3**. The starting dates of the three waves were June 21, 2020, October 12, 2020, and March 31, 2021 (**Table 1**). Therefore, each CT has its own unique pandemic profile, as indicated by the four representative CTs in **Figure 4**.

Finally, all this information was used for statistical, graphical, and cartographic analyses, to try to deeper understand the incidence on the different CTs of Malaga. The unit of spatial reference was the CT, the same spatial unit used in the vulnerability index previously described.

3.3. Methods

Cross-referencing information from the vulnerability index with information on the waves of COVID-19 required the generation of a method that considered spatial and temporal variables. In the last decade, there has been an increased interest in the cluster approach as a regional development tool despite its non-parametric character. In general, parametric measures have been used for regions with relatively reliable and continuous information sources, whereas non-parametric measures have been used in regions with lower-quality information (Nguimkeu and Tadadjeu 2021). However, the study of COVID-19 incidence have required the use of non-parametric statistics, as cluster technique to generate more robust and explanatory results without losing basic information (Khavarian-Garmsir, Sharifi and Moradpour 2021; Rahman 2021).
Most of the analysis regarding the incidence of COVID19 are using the accumulated incidence as the main measure to stablish incidences patterns (see for example Marí-Dell'Olmo et alt., 2021 in Barcelona case), but it has been shown how these patterns are also changing in time, as for example in Galacho-Jiménez et alt., 2022 or in Bárcena-Martín et al.t, 2022. In these papers it was shown how the incidence patterns are changing along the time, and so a tempo-spatial analysis is more appropriate than

spatial analysis using only accumulated incidence through the whole pandemic. This means, that, for example, in the locations shown in **Figure 4** the accumulated incidence through the whole period could be similar in the four cases, but clearly the peaks and valleys (this is, the patterns) are so different for the four cases. To find and analyze these tempo-spatial patterns, we must compare the 434 incidence curves through the 392 days of the pandemic (during the period of March 5, 2020 to March 31, 2021), to find common and simultaneous features in these temporal series. And, to this aim, we are going to use a clustering method, the K-means method, implemented using the Python package Kmeans. The K-means method (Hartigan and Wong, 1979) is one of the most widely used clustering methods (Ja-Shen et al. 2004). It aims to partition a set of n observations into k groups, in which each observation belongs to the group whose mean value is the closest. This method has been used in diverse fields, (e.g., as market segmentation (Lichtenstein et alt, 1997), computer vision (Frigui and Krishnapuram, 1999), geostatistics (Fouedjio, 2016), astronomy (Jang and Hendry, 2007)), data mining (Berkhin, 2006) even in the study of the home dwell time during COVID-19 (Huang et al, 2020).

In our case, the K-means algorithm was applied to the matrix of Euclidean distances between all the pairs of CT curves. Because each CT curve can be considered a 392-dimensional vector, the Euclidean distance in that 392-dimensional space was used to determine the similarity of each pair of curves; this is, to determine common and simultaneous features among these 434 temporal curves. Initial testing of different values for k (number of clusters) led to a selection of 5, because a k of 6 led to a very small number of members, preventing general conclusions about relationships.

For this methodology, we selected the number of clusters (k) using the well-known Elbow Method, that tries to minimize the within-cluster sum of squared errors

(WSS). The idea behind this method is looking at the total WSS as a function of the number of clusters and choose a number of clusters so that adding another cluster doesn't improve the total WSS. **Figure 5** is a plot of the WSS curve according to the number of clusters k.

In this curve, it is shown how from k=5, the improve of the WSS starts to be rather marginal. On the other hand, another important aspect when choosing k is the size of the resulting clusters. In order to obtain general conclusions when studying the resulting clusters, is so important to avoid having too small clusters, because the obtained conclusions will be marginal and so less interesting. So, together with the WSS, we are considering the cardinal (size) of the smallest cluster for each value of k, to avoid choosing a number of clusters generating marginal clusters, this is, too small cluster, that are not useful for generalizing purposes.

Figure 6 is including the WSS value and the size of the smallest cluster for each k. Again, from k=5 the size of the smallest cluster is dropping from 17 to 2. This is, when k is greater than 5 we start to have clusters with size 2 or less, that are not useful to obtain general conclusions from its information. For these reasons, we adopted k=5 as the optimal value for our analysis, as k=5 was shown to be the best option when considering the minimization of the WSS value and avoiding too small clusters.

4. Results

The geospatial and temporal analysis obtained five clusters based on the Euclidian distance between each pair of the COVID-19 time-evolution curves for each CT, that are shown in **Figure 7.** This clusters are built only according to the COVID-19 data, but examining the vulnerability values on each cluster, we tried to stablish relations with the COVID-19 tempo-spatial profiles on that clusters. Note that these relations will not only be spatial but also temporal, as the clusters are built considering the daily COVID-19 curves. So is, including the time-moving patterns detected on previous studies (Galacho-Jiménez et alt., 2022; Bárcena-Martín et al.t, 2022), where the correlation analysis showed that there is not a time-constant relation between vulnerability and COVID-19 incidence. Within this analysis, we tried to find common vulnerability features among the CTs showing a common temporal COVID-19 evolution, this is, with those CTs being on the same cluster.

Our results indicated a clear distinction of the most vulnerable CTs (clusters 1, 3 and 4) from the least vulnerable CTs (clusters 2 and 5). We therefore analyzed these two groups separately, starting with the least vulnerable CTs (**Figure 8**). These least vulnerable CTs were in cluster 2 (which has many elderly people) and cluster 5 (which has many young people).

Cluster 2 (elderly and upper class) includes CTs with the best socioeconomic conditions and quality of care (high income, high work intensity, advanced education, and little need for social interventions or material needs). However, it is also a demographically vulnerable population, mainly because many of these individuals are elderly and live alone. Some of the CTs in this cluster have less than ~~ideal~~ average environmental conditions due to temperature, slope, and poor access to services, although this cluster has the largest home size. This cluster includes neighborhoods in the eastern part of Malaga and parts of the historic center, as well as some areas of Teatinos and the west coast. It is the second largest cluster.

Overall, the CTs in cluster 2 had a low incidence of COVID-19 and the number of cases remained low during almost all the waves, although there was a slightly increased incidence during the fourth wave. It should be noted that although the pandemic curves for this cluster had lower maxima, they maintained higher for longer time.

Cluster 5 (young upper-middle class) had positive conditions in all the vulnerability sub-indices and in almost all the variables studied. These CTs include neighborhoods with a medium-high income, high labor intensity, low unemployment rate, low social care needs, and young age. These CTs are distributed throughout Malaga and, although they are not in the most environmentally benign areas, they are in regions with good environmental conditions, but there is also a significant concentration on slopes and in areas affected by flooding. This is the third largest of the five clusters, and mainly consists of young upper middle-class individuals.

The incidence of COVID-19 in cluster 5 increased during the different waves, with considerable intensity and slow recovery after the wave passed. The ~~SCs~~ CTs in this cluster seemed to be first affected by the different waves, but were also the first to experience resolution. It seems these neighborhoods had high resilience. The main reason to explain these high rates on COVID-19 on a non-vulnerable population could be mobility. These cluster is made up of young upper-middle class population, who travels more than average population, not only due to labor reasons, but also on holidays. On the other hand, most of the medical professionals lie on this upper middle-class, and they are more exposed to COVID infection.

We then examined the three clusters with the most vulnerability (**Figure ~~5~~ 9**). Cluster 1 (lower-middle class) includes ~~SCs~~ CTs with moderate socioeconomic status, welfare vulnerability, and low income levels and work intensity. The population is young, although life expectancy is lower than in clusters 2 and 5. These individuals make intensive use of social services, despite having low rates of dependency and being young. On the other hand, the environmental conditions of the neighborhoods were not bad, despite the small house sizes, and many of the homes are located in coastal areas or in the foothills of mountains. This is the largest cluster and, according to income level, these individuals would be classified as middle class or lower-middle class.

In these ~~SCs~~ CTs, the incidence of COVID-19 was very high during the fourth wave, with a moderate increase before the maximum and a moderate decrease after the maximum, but a lower maximum than cluster 5, perhaps because of the higher rate of social public care.

Cluster 3 (young lower middle class) includes CTs with greater socioeconomic vulnerability than cluster 1, and includes individuals with low income, very low labor intensity and a high value on severe material deprivation. This cluster is younger than cluster 1, with a lower dependency ratio, and older people who live alone. It also included ~~SCs~~ CTs in which the family units consisted of parents who are unemployed and have greater material deprivation. However, the individuals in this cluster make less use of social services than those in cluster 1, perhaps because these people are in more isolated areas and have less education. These CTs include neighborhoods scattered throughout Malaga, on the urban periphery, and in working-class neighborhoods of western Malaga.

The pandemic manifested slowly in the CTs of this cluster, although there was a much greater increase in incidence during the fourth wave than in cluster 1, 2, and 5. As shown in the contagion curves, the contagion in these most vulnerable communities is slow at the beginning, but the affection is higher after some time. It means that the initial contagions are found in the less vulnerable areas, probably due to their higher mobility, for labor and leisure reasons, and to the fact that the sanitary workers are more likely to be found on less vulnerable community. These facts have been already shown before in the literature: the higher geographical mobility of middle- and high-income individuals in rich countries, for leisure or business travel (Bonaccio et al., 2020); or the higher proportion of workers in occupations most likely to be exposed such as doctors or nurses, who generally have a high socioeconomic status (Public Health England, 2020). Hospitals also have been shown as major carriers of Covid-19 over the first phase of the pandemic, as they quickly become populated with infected patients, facilitating transmission to uninfected patients and doctors and nurses (Nacoti et al., 2020). So, the initial contagions look to appear more likely on middle class areas, being then the more vulnerable areas less affected at the beginning. But, once the virus starts to spread to the rest of the population (more vulnerable), their living conditions are worse to stop this spread, due, for example, to a higher density of population, and then the contagion starts to be faster and higher in these areas.

Cluster 4 (elderly lower class) includes a small number of CTs, but these CTs were highly vulnerable. They are in neighborhoods with the poorest people, the lowest incomes, low labor intensity indexes, significant need for social services, and significant dependency rates. Although the age was not very high, it was older than cluster 3. These CTs are in neighborhoods near the Natural Park, so have a high risk of flooding.

The neighborhoods in cluster 4 experienced the largest peaks during all four waves. During the fourth wave, the incidence increased up to about 25 cases per 1000. Although the decline after the fourth wave was rapid, it was less rapid than for cluster 3.

Analysis of all five clusters indicated that cluster 4 had the greatest vulnerability, in that it had the greatest number of cases during each wave (**Figure** 10). Cluster 2 was the least vulnerable, and even though it had an elderly population the number of cases was low during all waves. On the contrary, cluster 5, which consisted of young and vulnerable individuals, seemed to have had high levels of disease during the initial waves, with maxima earlier than other clusters. However, this cluster had fewer cases during the fourth wave compared to other neighborhoods that were young but more vulnerable.

These results indicated that CTs with older people responded differently according to their vulnerability. The least vulnerable had fewer infections, and these elderly people mostly remained safe and protected; however, the elderly from the most vulnerable neighborhoods had the greatest number of infections and were most affected by each of the four waves.

Interestingly, the younger CTs that were least vulnerable seemed to develop maxima earlier than the other clusters, but in a more controlled way, except during the first wave. Among the young clusters, cluster 3 had the worst outcome, probably because many of these families live in small houses, have low work intensity, and experience severe material deprivation.

We also analyzed the time of onset and the time when decline began during each of the three waves. (**Table 2**).

Cluster 5 (young upper-middle class) had the first onset in wave 1 (day 64) and wave 3 (day 346). Because the second wave consisted of two concatenated waves, the clusters had somewhat different behaviors at that time. Below, we also considered the maximum of each cluster during each wave. After the onset of wave 1 in cluster 5, the COVID-19 wave began to appear in the other clusters, starting with the youngest cluster and ending with the oldest cluster. Thus, cluster 4 (elderly and lower class) had the last onset (day 74) and the highest maximum (**Figure 11**) for wave 1.

During the second wave, cluster 4 (elderly and lower class) had the most infections, and cluster 2 (elderly and upper class) had the fewest (Figure 12). Cluster 5 (young and upper-middle class) had fewer infections, a later onset, and a rapid decline.

During the third and most severe wave, cluster 4 (elderly and lower class) again fared the worst, and cluster 5 (young and upper-middle class) had the first onset and the most rapid decline (Figure 13). Cluster 3 (young and lower-middle class) had a later onset, but a higher maximum, and a slower decline than clusters 1, 2, and 5.

5. Discussion

COVID 19 has been a severe setback to sustainable development throughout the world. Numerous authors proposed that only an integrated and holistic analysis of current policies will be able to restore the goals for the future proposed in the United Nations 2030 Agenda (Sachs et al., 2020).

Quitar de las referencias: Hallencreutz, D., & Lundequist, P. E. R. (2003). Spatial clustering and the potential for policy practice: Experiences from cluster-building processes in Sweden. European Planning Studies, 11(5), 533-547.

In these analysis, clustering has been demonstrated to be an useful tool. In Fransiska, H. (2021), author used clustering to classify Indonesian provinces according to their COVID mortality, to help authorities to design their policies. In Ojua et al. (2022) they implemented a K-means cluster analysis for the effective distribution of medial supplies and policy making during the pandemic in Nigeria. Analogously, Huang et alt. (2020) used also a K-means clustering approach to show how demographic/socioeconomic variables can explain the disparity in home dwell time in response to the stay-at-home order. Their study revealed that in Metro Atlanta the long-standing inequity issue in the U.S. stands in the way of the effective implementation of social distancing measures.

In many cities, the pandemic reinforced the need to analyze data at the micro-scale to develop effective solutions to the problems and needs of the entire population, especially the most vulnerable groups (Acuto et al., 2021). There have been glaring deficiencies in the availability of reliable data on the impact and scope of COVID-19 in vulnerable populations. In the case of Malaga, we were able to build a database using information provided by the Junta de Andalucía. However, during the first waves of the pandemic there were not enough tests available and many possibly infected individuals remained in their homes and were not registered. This reduced the reliability of some of our results and limited our ability to reach definitive conclusions.

On the other hand, our analysis of urban vulnerability based on composite indicators was also used by many previous researchers (see, for instance, Egea Jiménez et al., 2008; Ayuntamiento de Madrid, 2018, Bárcena-Martín et alt., 2022). In the case of Malaga, we used a system that was established based on available census information. The global vulnerability index that we used (Bárcena- Martín et al., 2021) provides a ‘snap shot’ of the status of neighborhoods, although many changes occurred during the waves of the COVID-19 pandemic. Ideally, we should assess vulnerability before, during, and after the pandemic, and identify new variables that allow the construction of a more dynamic vulnerability index. Besides, such a more dynamic index could let as analyze another important feature within the COVID pandemic, the sanitary and socio-economic resilience among the different communities, that is something that cannot be properly studied with this kind of index.

We therefore suggest that future research in this area should include variables related to the labor market, which can vary on a monthly basis, and population mobility (which could be determined by use of mobile devices, Kolesnichenko et al., 2021). Likewise, given the metropolitan nature of the city of Malaga and the importance of population mobility for disease transmission, COVID-19 indexes and data for other municipalities around the capital should be included in future research, as we must assume that people living in the metropolitan area played also an important role on the COVID spread.

Finally, we chose Málaga as a case study because it is the second biggest city in the south of Spain, our region, but there's a lack of research on the rural and more isolated areas. It would be so interesting to explore the spread out of the main cities, and compare the results with the metropolitan areas, to more deeply understand the key factors and the socio-economic consequences of the COVID spread.

6. Conclusions

As Adams (2017) indicated, achieving the goals of the United Nations 2030 Agenda requires the development of tools that measure the multidimensional nature of sustainability, and allow a reliable characterization of the initial situation and the results of an intervention. The present research focused on the conditions of the current population and demonstrated the importance of spatial analysis for locating the most vulnerable groups so that appropriate policies can be implemented.

Furthermore, we observed that assessment of global vulnerability requires a detailed spatial analysis, and also a sectoral analysis that considers economic, social, environmental, welfare vulnerability, medical and similar variables. Only in this way will it be possible to design spatially integrated policies, plans, and projects that correct underlying structural inequalities (Ludovic et al, 2022).

Stiglitz (2020) and other authors emphasized that COVID-19, like many other crises, did not affect everyone equally, and that the most vulnerable groups suffered the most in terms of health consequences and subsequent economic effects. Our results indicated that this interpretation also applies to Malaga. In particular, the most vulnerable neighborhoods were those most affected by the COVID 19 pandemic. It may seem counterintuitive that the pandemic began in neighborhoods that had more socioeconomic resources and a younger population. However, this may be because this population travels more and includes many employees in the health sector, who may have been exposed to COVID-19. However, the virus has been more devastating in neighborhoods that have elderly people who live under the worst socioeconomic conditions. Our use of a small spatial reference unit — the CT — greatly facilitated our identification of the most affected groups.

Our results thus emphasize the importance of considering the spatial and temporal scale for analysis of planning strategies and evaluation of urban policies. The use of geographic information systems and the construction of indices from different sectoral indices is an effective approach for these analyses that should be more widely used to address similar problems in other areas.

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Disclosure statement

The authors report there are no competing interest to declare.

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[redacted]		
till day 172	till day 344	till day 455
21/6/20	10/12/20	31/3/21

Table 1. Dates considered as the beginning of each wave of the epidemic.

Source: Own elaboration

	Onset	Decline	Onset	Decline	Onset	Decline
Cluster1	**64**	92	216	323	366	400
Cluster2	71	95	**203**	318	363	391
Cluster3	67	94	219	323	352	398
Cluster4	74	**91**	220	**315**	367	395
Cluster5	**64**	**91**	216	324	**346**	**388**

Table 2. Day of wave onset and day when the wave began to decline during the three waves of COVID-19 in the five clusters. Note: Bold numbers indicate clusters with the earliest times. Onset: day of wave onset; Decline: day when the wave began to decline.
Source: Own elaboration

Figure captions

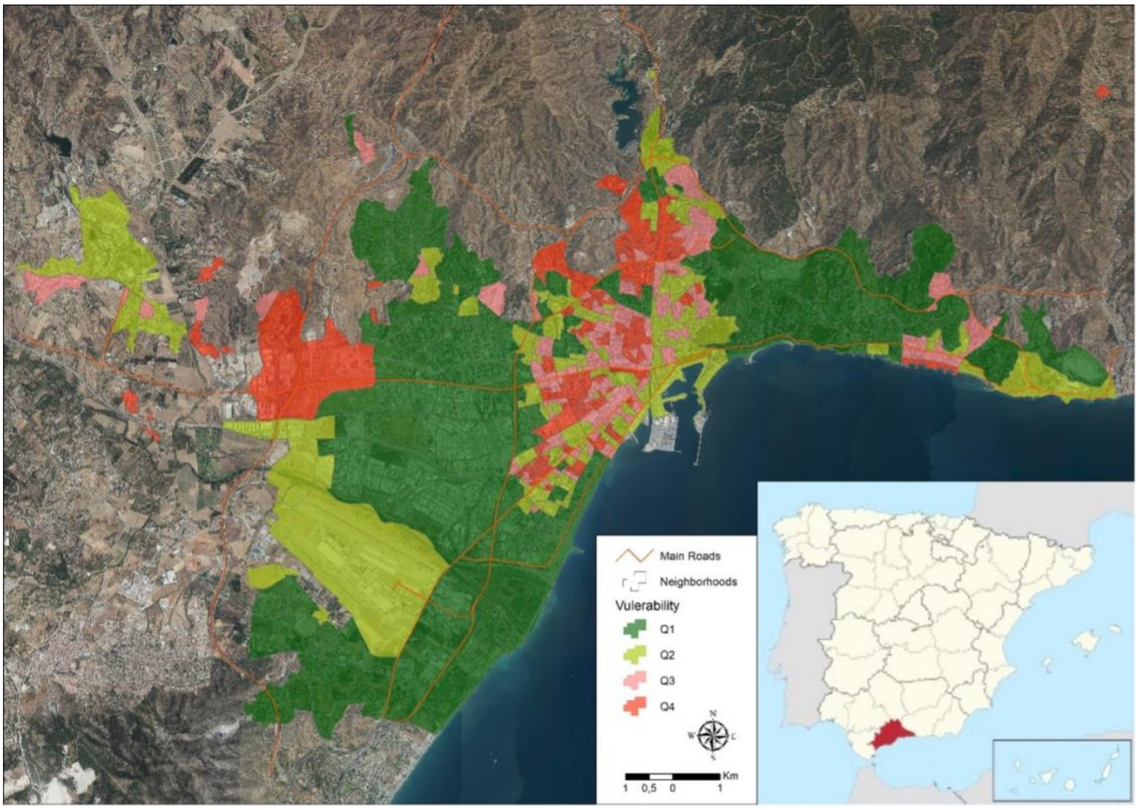

Figure 1. Vulnerability in Malaga's census sections by quartile. Q1 includes the 25% of census tracts with the lower vulnerability, Q2 include the following 25% of census tracts ordered from the lower to the higher vulnerability, Q3 the following 25% selected in the same way and finally Q4 is the 25% of census tracts with the highest vulnerability.

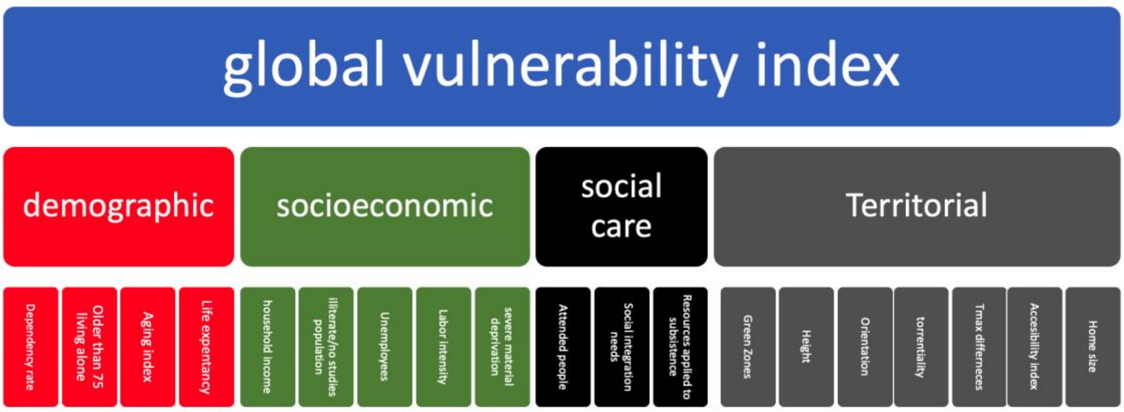

Figure 2. Variables and sub-indices of the vulnerability index of neighborhoods in Malaga.

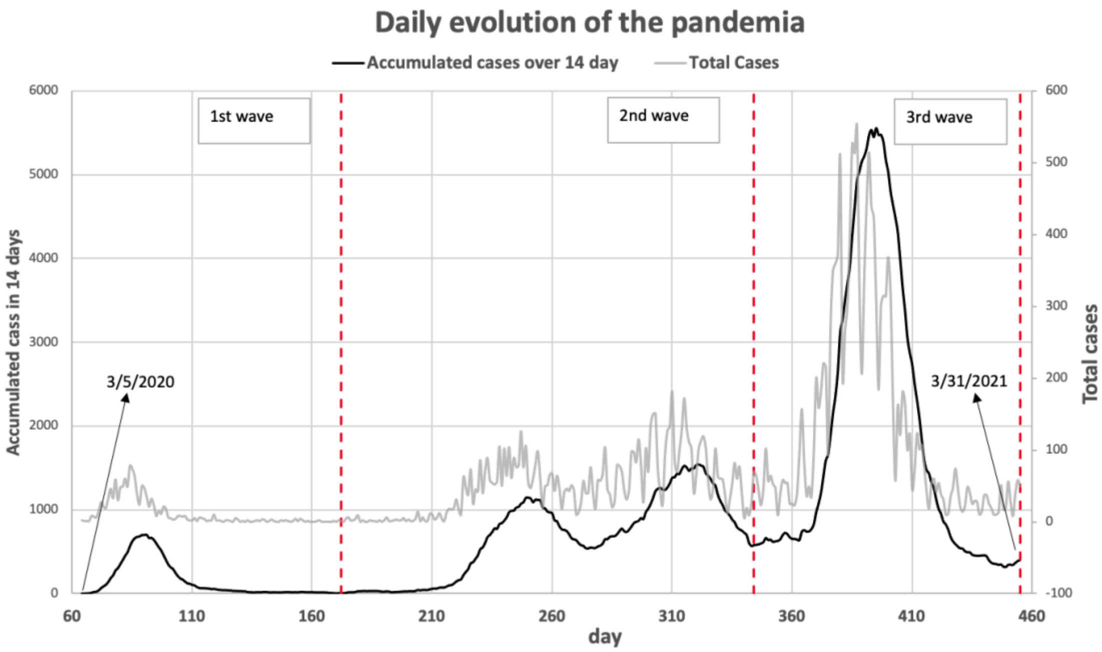

Figure 3. Daily number of COVID-19 cases in Malaga from March 5, 2020 (day 64) to March 31, 2021 (day 455).

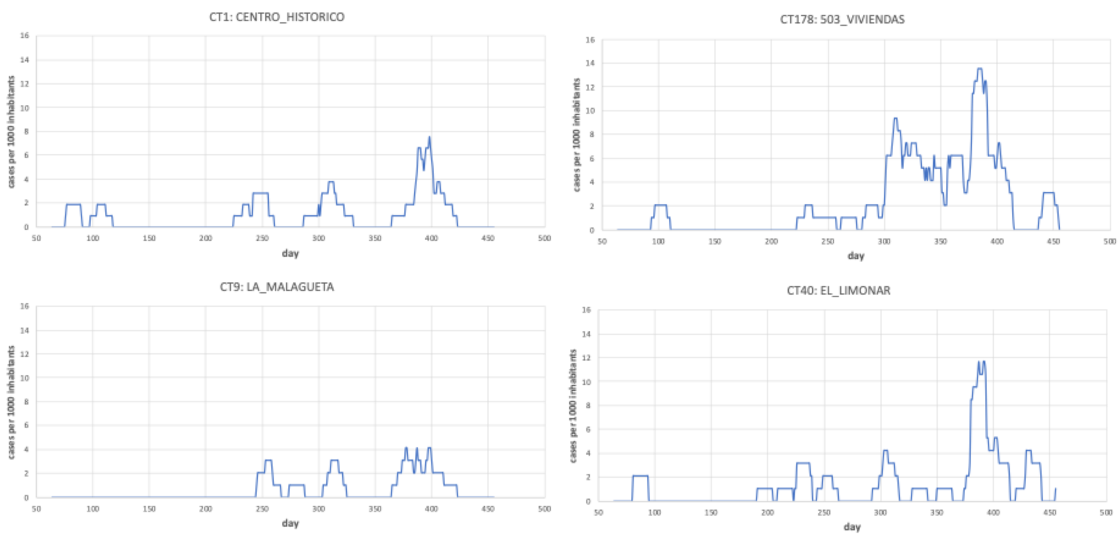

Figure 4. 14-day accumulated cases of COVID-19 in four representative CTs.

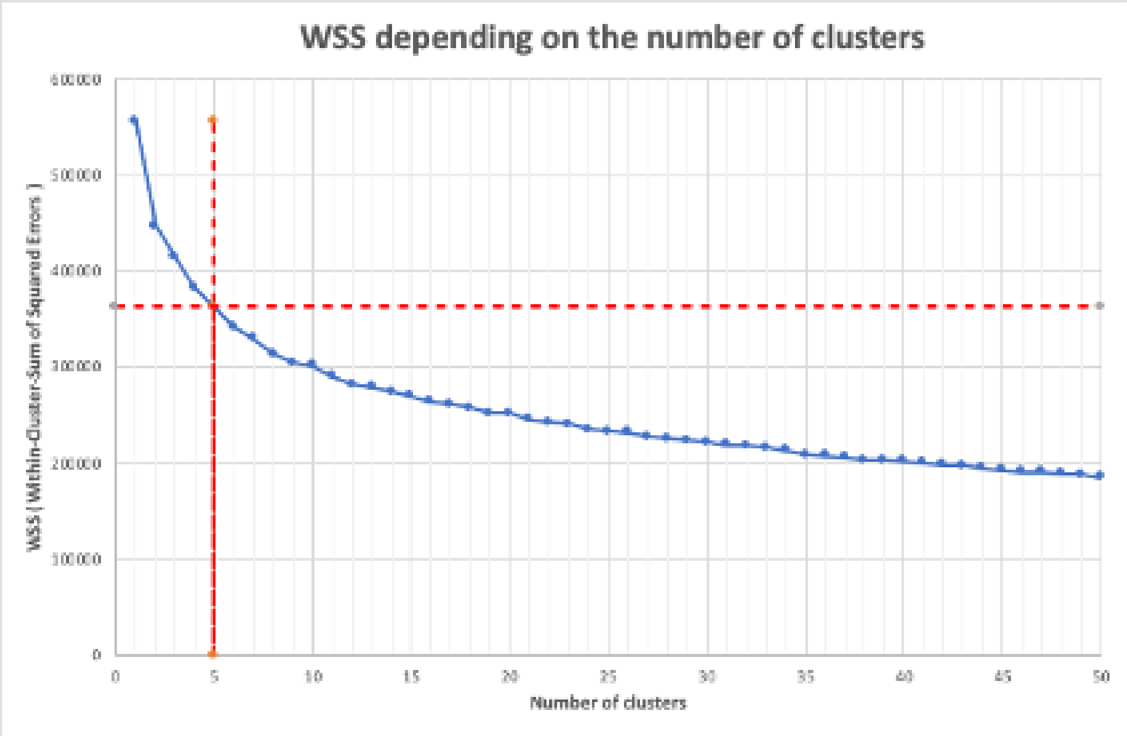

Figure 5. WSS depending on the number of clusters.

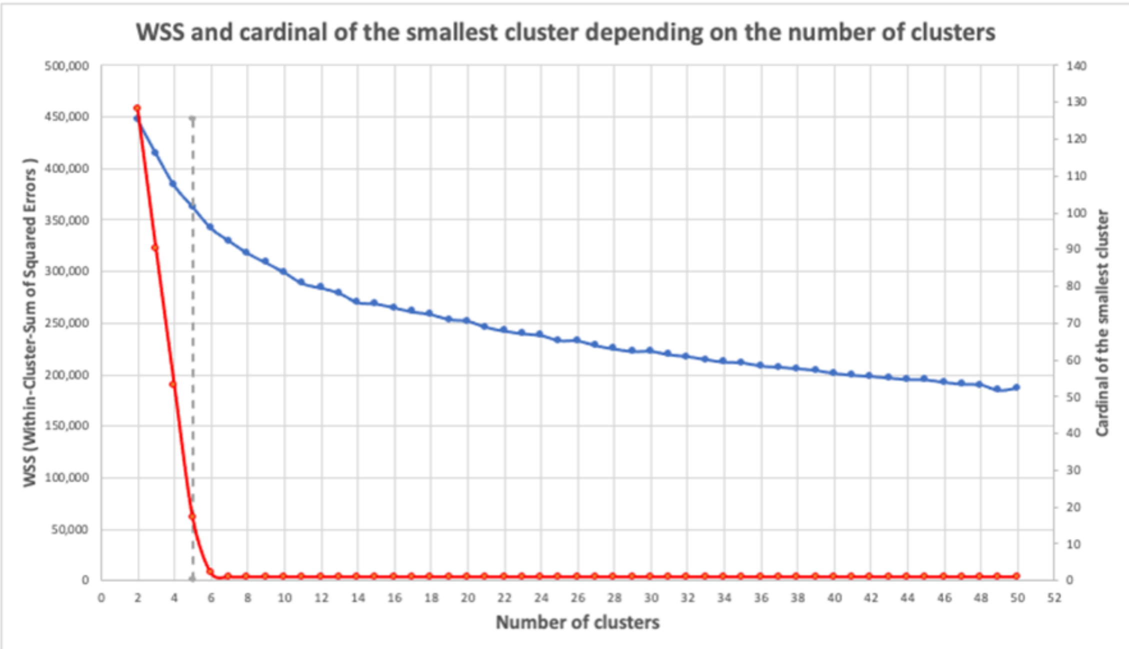

Figure 6. WSS and size of the smallest cluster depending on the number of clusters.

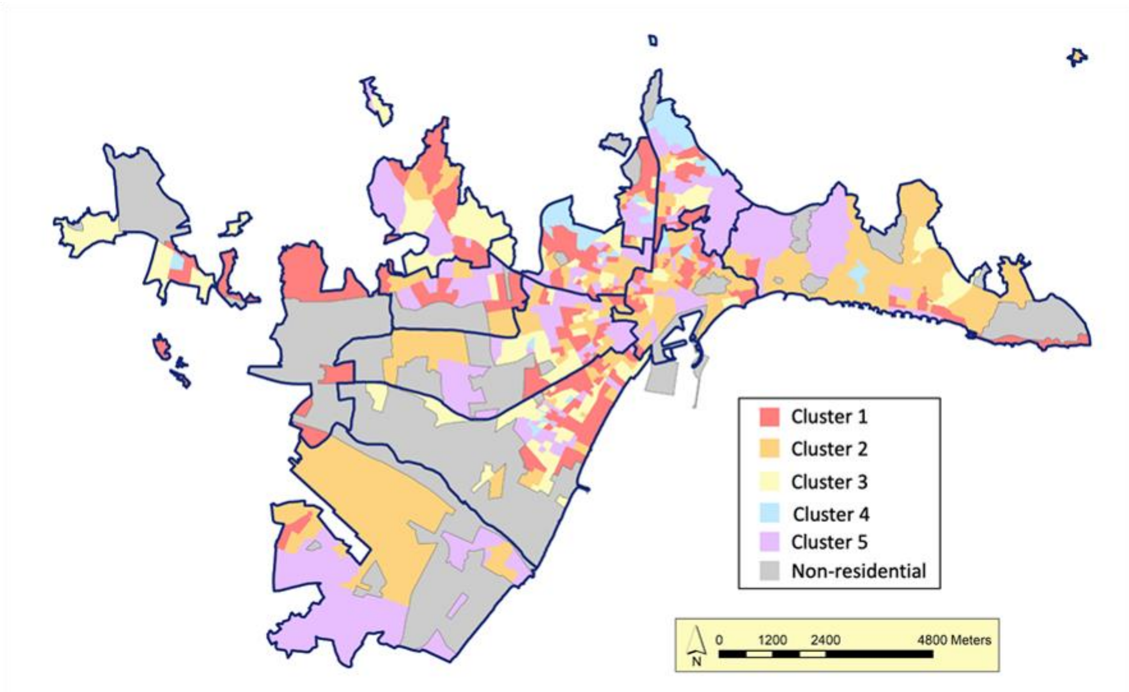

Figure 7. Distribution of the CTs of each cluster.

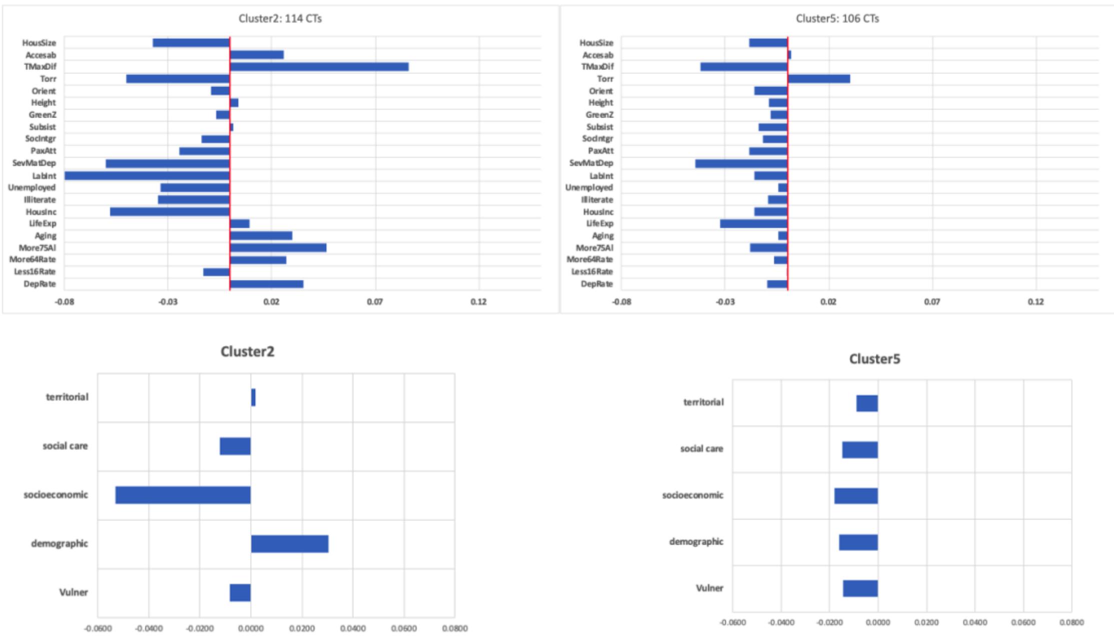

Figure 8. Vulnerability variables and indices of the least vulnerable CTs (clusters 2 and 5)

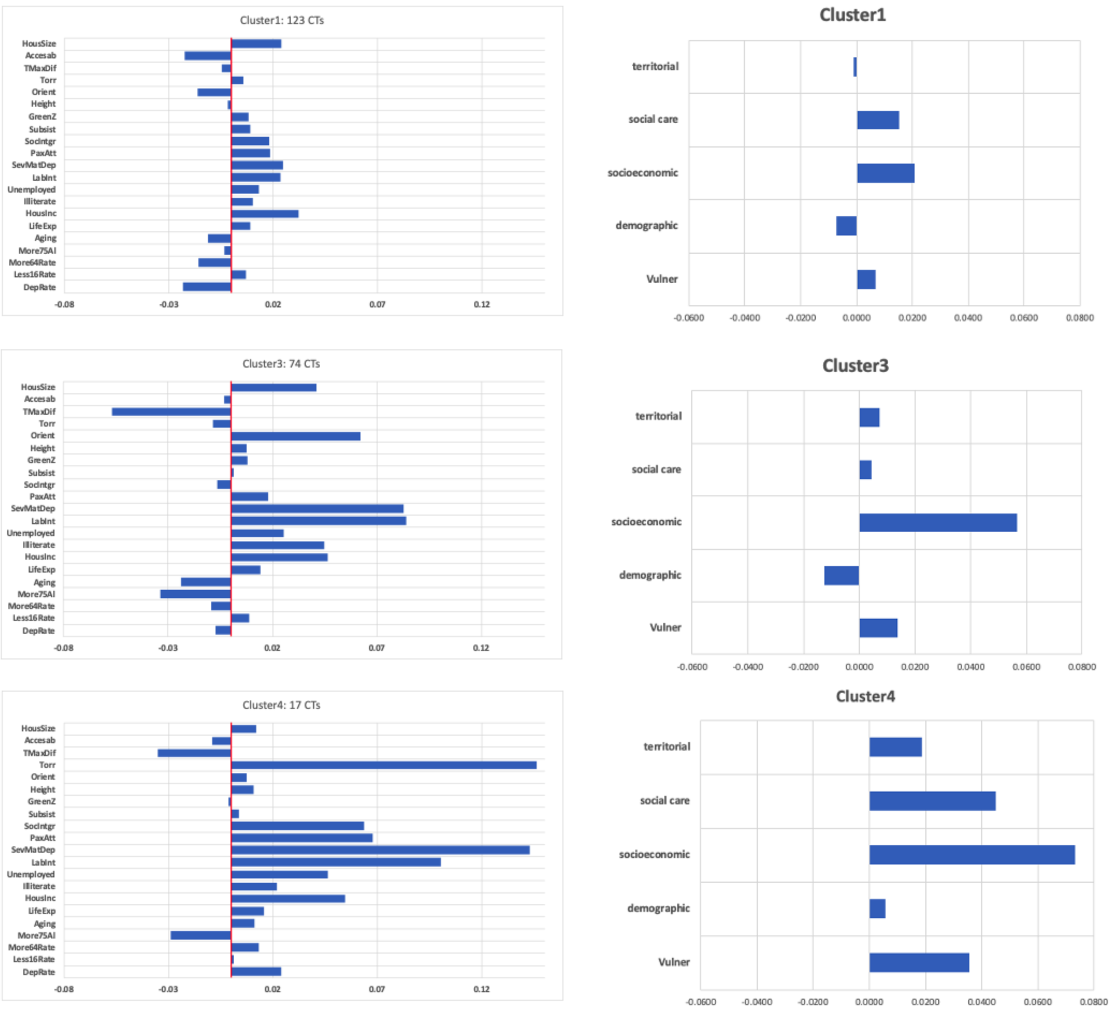

Figure 9. Vulnerability variables and indices of the most vulnerable neighborhoods (clusters 1, 3 and 4)

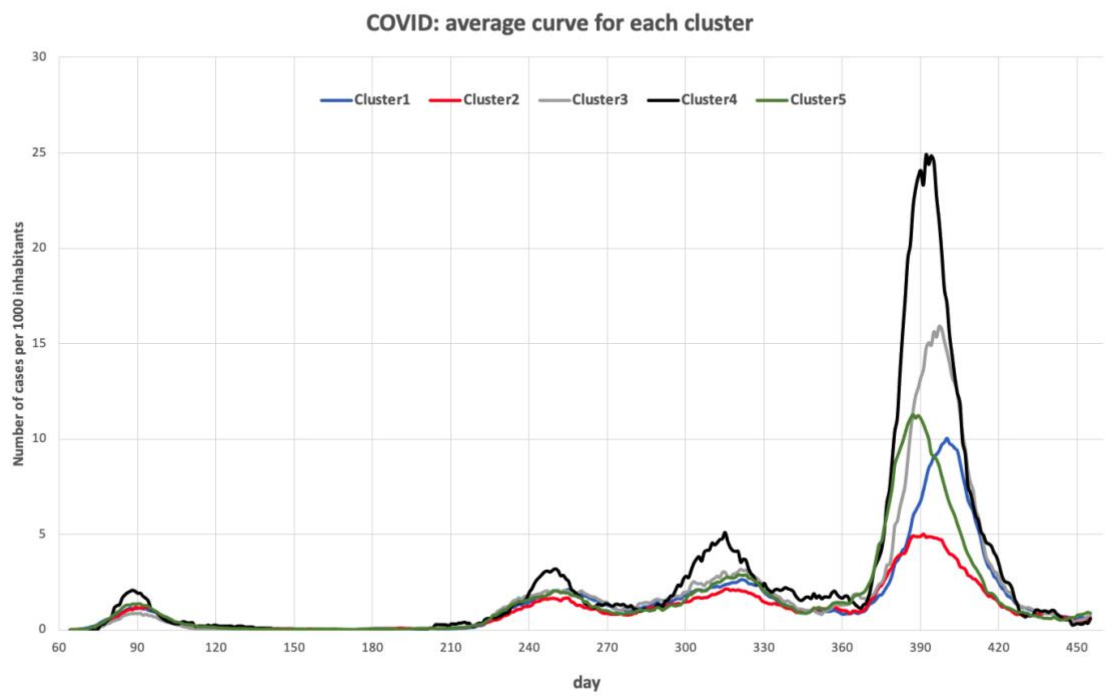

Figure 10. Number of cases per 1000 inhabitants in each cluster during the waves of the COVID-19 pandemic.

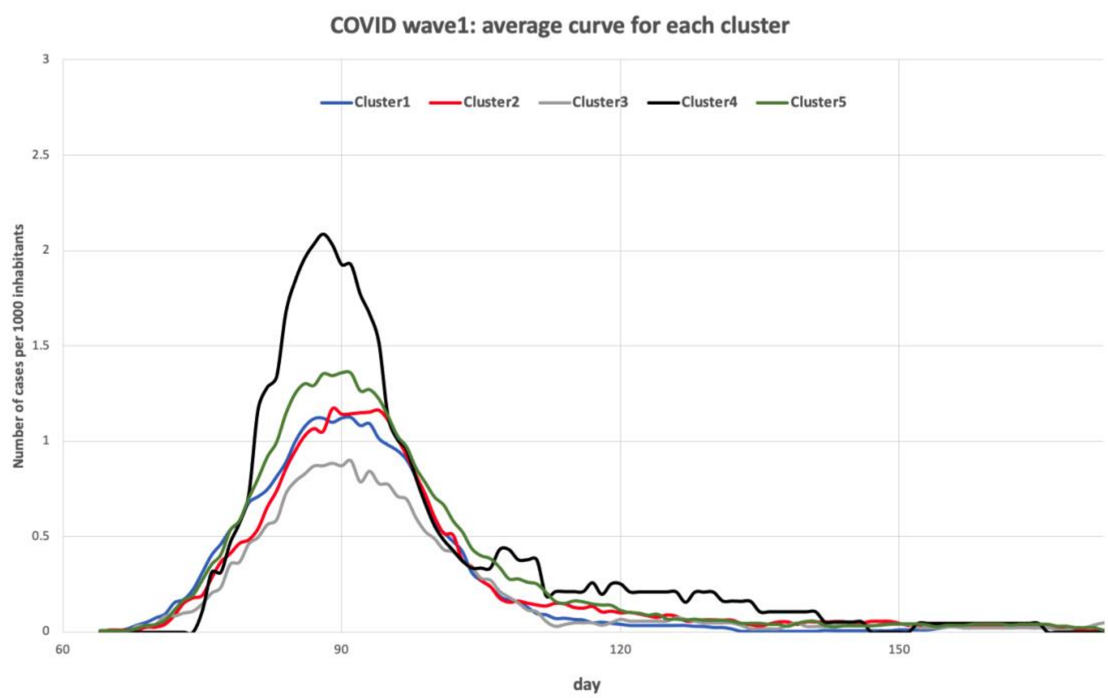

Figure 11. Number of cases per 1000 inhabitants in each cluster during the first wave of the COVID-19 pandemic.

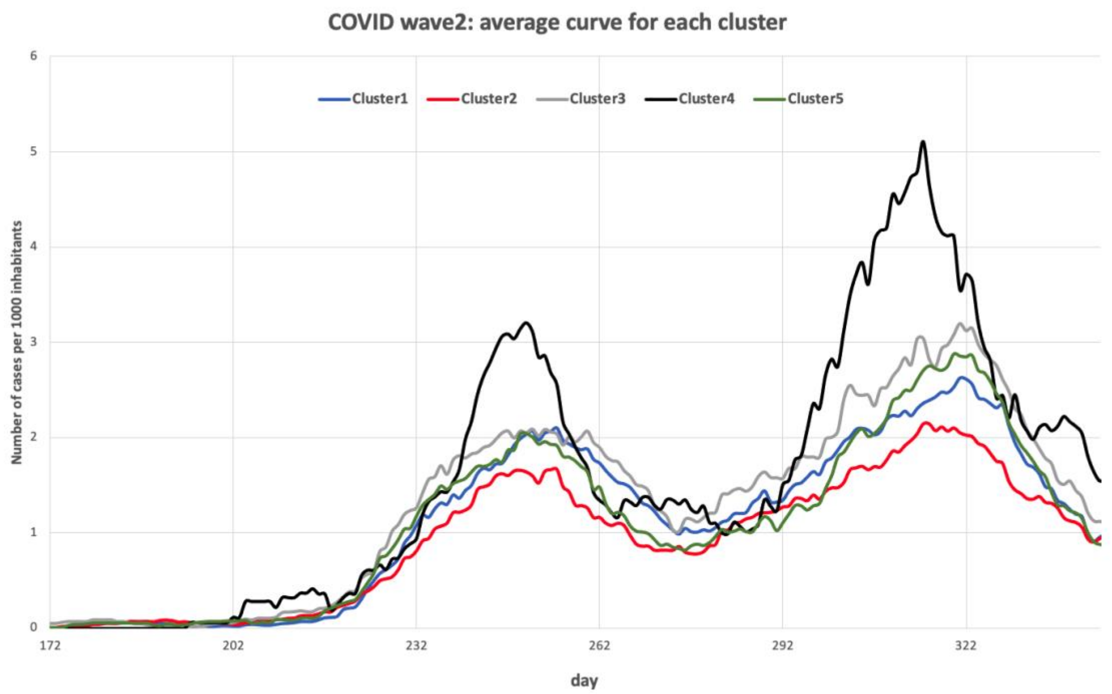

Figure 12. Number of cases per 1000 inhabitants in each cluster during the second wave of the COVID-19 pandemic.

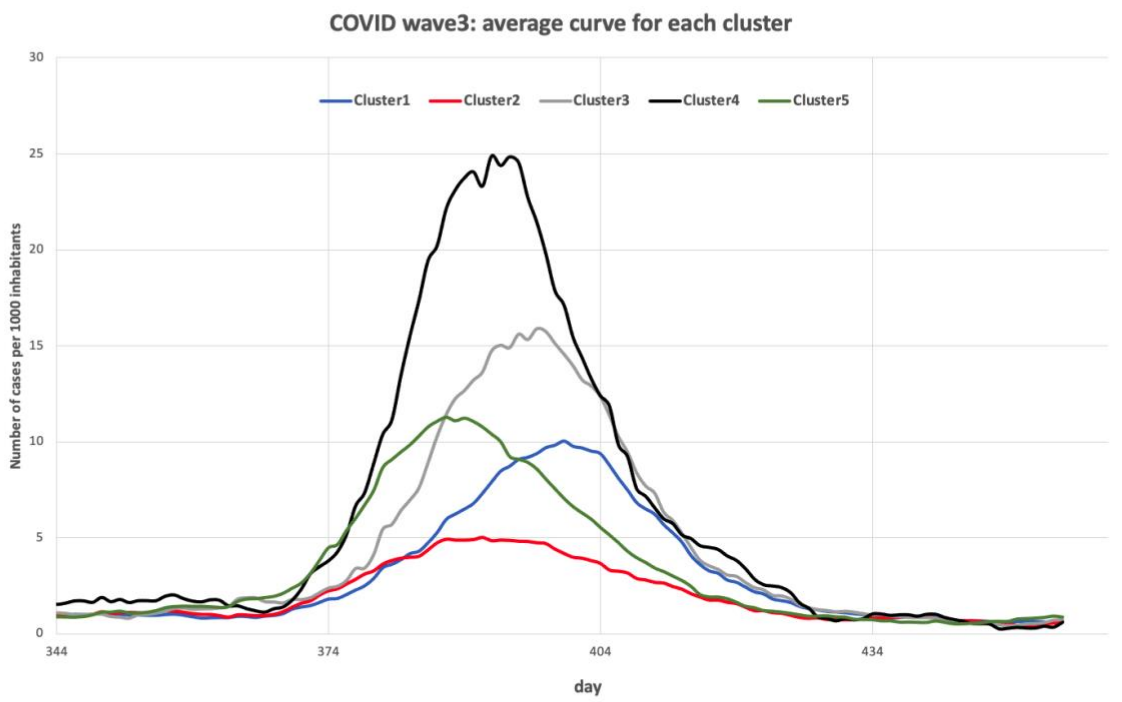

Figure 13. Number of cases per 1000 inhabitants in each cluster during the third wave of the COVID-19 pandemic.