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Grazia Brunetta
Patrizia Lombardi
Angioletta Voghera *Editors*

Post Un-Lock

From Territorial Vulnerabilities to Local Resilience

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Post Un-Lock

From Territorial Vulnerabilities to Local Resilience

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Preface

This book is the first result of the "Post Un-Lock" research project, funded by the Interuniversity Department of Regional and Urban Studies and Planning (DIST) of the Politecnico di Torino, a three-year work involving the collaboration of a large number of researchers belonging not only to different departments and institutions but also to diverse disciplinary areas.

The research involves teams from the Department of Environmental, Land, and Infrastructure Engineering (DIATI) of the Politecnico di Torino (such as environmental and geomatics engineers), the Department of Mathematical Sciences "Giuseppe Luigi Lagrange" (experts in mathematical statistics), and the Department of Medical Sciences of the Università di Torino (researchers in the field of medical statistics and epidemiology), committed to reflecting on the territorialization of the pandemic and the effects of pollution on health in cities.

The Post Un-Lock research took shape in the last months of 2020, triggered by the scientific impulse of the international goals of sustainability and resilience in the perspective of the post-carbon city and the overcoming of environmental, economic, social and health crises. Scholars have collaborated and tested on case studies methodologies, approaches, and tools capable of re-imagining cities and regions to overcome vulnerabilities and to innovate the socio-ecological system on the basis of the ideal-typical model of Local Resilience Unit.

With this in mind, we would like to thank, in addition to the authors of the chapters and their collaborators: the partners of the research such as the Interdepartmental Centre Responsible Risk Resilience Centre (R3C), the SDG11LAB, the S3+Lab (Urban Sustainability and Security Laboratory for Social Challenges), the CED PPN (European Documentation Center on Natural Park Planning), the Living Lab and the PIC4SER of Politecnico di Torino. We would also like to thank the external supporting institutions such as IUGA of Grenoble, University of South Denmark, CMCC (Euro-Mediterranean Center on Climate Change), and the administrations involved in the case studies, whose suggestions provided crucial support for the outcomes of this publication. Other institutions and people we would like to thank are: Nicola Tollin, Professor with special responsibilities in Urban Resilience, UNESCO Chair at University of Southern Denmark (SDU), ITI,

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Turin, Italy
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Grazia Brunetta
Patrizia Lombardi
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Part II
Topics

Chapter 2
Notes on Spatial Implications of COVID-19. Evidence from Piedmont Region, Italy



Grazia Brunetta, Ombretta Caldarice, Danial Mohabat Doost, and Franco Pellerey

Abstract The COVID-19 pandemic has been studied by many scholars from a wide range of disciplines. Among these investigations, planners and regional scientists have researched the spatial spread of the contagion. Most of these studies tried to explore the spread of the disease in a fixed period, like annually, and analysed the spatial variables that are most influential on the COVID-19 spread over territories. On the same line, the chapter investigates the pattern of virus transmission in the 1.181 municipalities of the Piedmont Region during two years of the pandemic over different periods by providing 24 monthly and two annual hot spot maps using the Spatial Statistics Tools on ArcGIS. Consequently, the chapter analyses the correlation between the spread of contagion with three spatial variables (population density, annual average traffic flow, and the ageing index) by performing a statistical analysis on the municipalities which showed unexpectedly higher or unexpectedly lower numbers of contagion. The results show that the impacts of population density and annual average traffic flow are verified on the transmission rate of the cities with unexpectedly higher or lower exposure to COVID-19 contagion than their neighbours both in the first and the second year of the pandemic. For the ageing index, an association is noticed during the first year while not confirmed for the second. In conclusion, the chapter proposes that studying the disease's variations—at different times and on a regional scale—uncovers the spatial dimension of the phenomenon and would suggest insights for both scientists and policymakers to enrich preparedness as the preferable approach in future planning policies towards transformative resilience.

Keywords COVID-19 pandemic · Transformative resilience · Piedmont region · Spatial planning · Geographic information system

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2.1 How Do Spatial Implications Matter in the COVID-19 Pandemic?

In his 2012 seminal book, David Quammen (2012) defines pandemics as *spillovers*, questioning if they are merely happening to us or if we are somehow causing them. Most recently, Nassim Taleb reminded us that the COVID-19 pandemic is not a *black swan* but a warning of a more fragile global system (Avishai 2020). Precisely for this reason, the ongoing COVID-19 crisis powerfully reveals its spatial implication (Coppola 2021). On the one hand, spatial relations can intensively contribute to the diffusion of the disease; on the other hand, this contribution might change over time during the pandemic, so both temporal and spatial dimensions are essential aspects to be studied.

Along this line, planners and regional scientists are currently engaged in addressing the COVID-19 physical dimension, as it is a phenomenon that establishes spatial features in addition to the human one (Allain-Dupré et al. 2020). Although the health effects of COVID-19 are not neglectable, the impacts on the population go beyond the spread of the disease.

In addition to the temporal dimension—that only a few recent kinds of research considered for analysing the pandemic's territorial changes—it is also helpful to find the most influential spatial variables that might contribute to the spread of infection. Despite the growing awareness about the spatial implication of COVID-19, a limited number of place-based studies have been published since the initial pandemic outbreak. Among the existing literature, some scholars traditionally relate density and crowding to the intensification of the disease spread (Wong and Li 2020), while a growing number of researchers suggest either weak, strong or even no correlation between density and COVID-19 spread (Carozzi et al. 2020). Many empirical researchers perform case study analyses at the national level to identify the role of density as a predictor of infection rates. Among those, Bhadra et al. (2021) suggest a moderate association between COVID-19 spread and density in India, while Kadi and Khelfaoui (2020) demonstrate a stronger correlation between the two in the case of Algeria. In addition to density, some other studies have attempted to reveal spatial parameters which can explain the diffusion of COVID-19. These factors mainly include connectivity and ageing. On this line, Hamidi et al. (2020) claim that connectivity matters more than density in the US spread of COVID-19, while Mollalo and Vahedi (2020) recognize ageing and demographic variables as central.

Turning to the Italian context, the empirical studies of COVID-19 partially concentrate on the spatial dimension of contagion. Buja et al. (2020) showed that the spread of COVID-19 was correlated negatively with the ageing index in provinces of Northern Italy, underlying that provinces with younger populations are more likely to be the hot spots for the rapid spread of the disease. Dettori et al. (2021) compared the pattern of COVID-19-related mortality in Italy with several geographical, environmental, and socioeconomic variables at the provincial level, demonstrating that contagious is related to pollutants and land take.

Starting from this broad framework, this chapter initially performs a territorial analysis on the increase of the pandemic using the GIS-based hot spot analysis regarding the spread of the COVID-19 infection in the 1.181 municipalities of the Piedmont Region by providing 24 monthly and two annual maps to track the movement of the disease outbreaks over time. The first set of results shows that the hot spots and cold spots of contagion are functions of both time and space, and different episodes move within the region. By changing the spatial scale of the analysis, it is observed that some municipalities—even inside the clusters of hot spots and cold spots—show an unexpectedly lower or higher contagion rate compared to their neighbours. Consequently, we analysed the correlation between the spread of contagion with three spatial variables (population density, annual average traffic flow, and the ageing index) by performing a statistical analysis on the municipalities which showed unexpectedly higher or unexpectedly lower numbers of contagion.

From this perspective, the chapter aims to fill the gap as there are no studies performed at the local level in Italy, to the best of our knowledge. Accordingly, the novelty of this study refers to its methodological approach in considering spatial and scalar factors of the pandemic in a way that:

- It is performed through a geostatistical analysis using GIS techniques and considering the proximity factors between municipalities.
- It is not merely limited to the analysis of density as a spatial variable, integrating connectivity and ageing as well.
- It is developed at the local scale, fitting the Italian planning system.

In the end, this study aims to suggest implications for policymakers to determine adequate courses of action to solve the problem or implement reforms independently from the pandemics, enriching preparedness (Balducci 2020) with an adaptation path in a "build back better" approach towards transformative resilience (Brunetta and Caldarice 2020).

2.2 Methodology

As mentioned earlier, this study performed a GIS-based geospatial analysis for 1.181 Piedmont Region municipalities located in northwest Italy with an area of 25,402 km^2, making it the second-largest region of the country, with more than 4 million population as of 31 January 2021. The Piedmont Region has eight provinces, including the metropolitan area of Turin and the city of Turin as the capital. The geographical divisions of the country, regions, provinces, and municipalities of the study area are visible in Fig. 2.1.

In Fig. 2.2, the methodological workflow of this study is presented, which consist in several steps, including data collection, data processing, applying the hot spot test to find out how clusters moved within the territory, performing EBK for finding the cities with unexpectedly higher or lower exposure to contagion, and analysing the

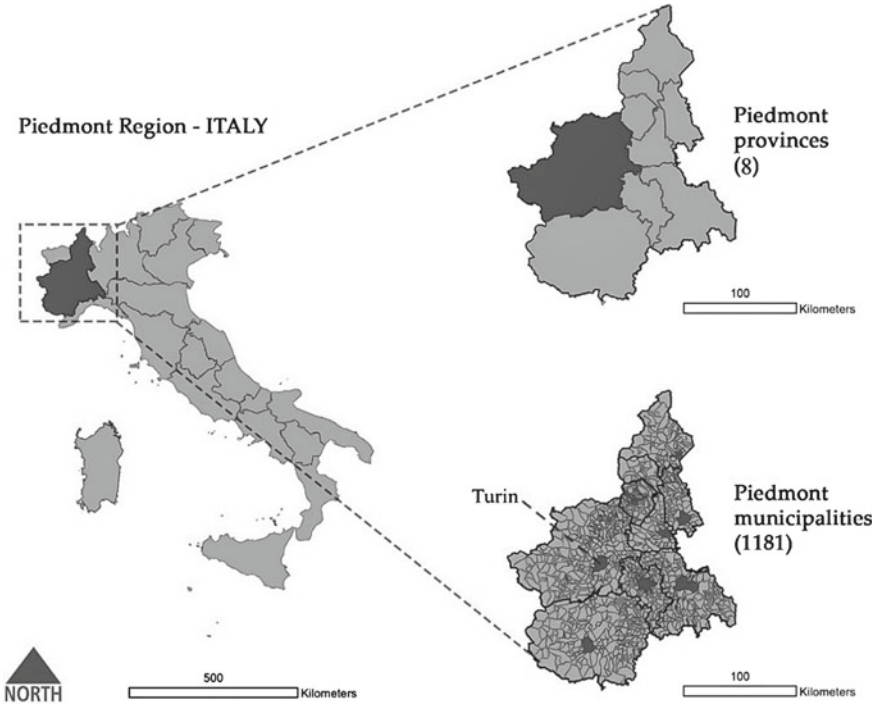


Fig. 2.1 Localization of the study area

territorial variables of these municipalities. All these steps will be explained in detail followingly.

As the first step, the raw data are extracted from the daily updated maps prepared and published every day by the Piedmont Region website. These daily updated maps provide the number of present-day positive cases in every 1.181 municipalities of the Piedmont Region. It is important to note that these numbers represent the new cases for each day besides those who tested positive in the previous days and are still positive. The data have been extracted from 26 March 2020 to the end of February 2022, enabling us to cover two years of the pandemic. In addition, the demographic and territorial data are compiled from the Italian National Institute of Statistics (ISTAT) data warehouse through an annual census survey updated on 1 January 2021. According to these data, unsurprisingly, the cities with more inhabitants are likely to contain more daily positive cases. Consequently, to enable the comparison between the exposure of cities to contagion, these absolute data have been converted into relative data by dividing the total number of positive cases by the number of inhabitants in each city. Subsequently, this number has been multiplied by 1000 to reach a more understandable indicator. In other words, the number of daily positive cases for 1000 inhabitants is calculated in every 1.181 municipalities. Afterwards, these relative daily data have been transformed into annual data by simply dividing

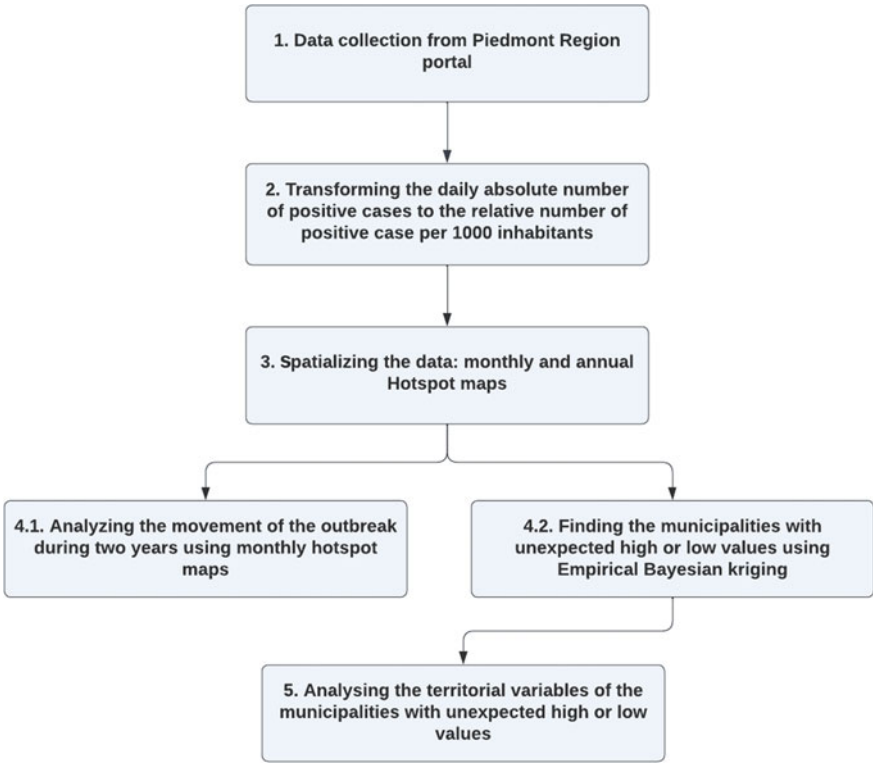


Fig. 2.2 Methodological workflow

the overmentioned indicator into the number of days each year. The output of this step was two sets of relative annual exposure to contagion (AEC_R) for every municipality during the first or second year of the pandemic. These data then became spatialized by matching the ISTAT code for each municipality to the shapefile provided by Piedmont Region Geoportal.

The first set of analysis dealt with the creation of 24 monthly and two annual maps of hot spots using the hot spot analysis tool available in Spatial Statistics Tools of ArcGIS. This tool operates by examining each characteristic in the light of its surrounding features. A feature must have a high value and be surrounded by enough features that have high values in order to be a statistically significant hot spot. The hot spot analysis helps to recognize the movement of the outbreaks within the territories.

Moreover, this study takes a closer look to the clusters of municipalities and finds out that some municipalities unexpectedly show a significantly different level of contagion compared to the surrounding municipalities. In order to find and locate these municipalities, in each of the two years, the data regarding the relative contagion have been interpolated by using the Empirical Bayesian Kriging (EBK) technique, which is available in ArcGIS Spatial Analyst Tools.

The Kriging method is an advanced interpolation tool, validated by Kyriakidis in 2004, for the estimation of disease frequency in the country scale (Kyriakidis 2004) that provides changes to the original data values considering the values in the neighbourhoods of the point and their mutual spatial correlation, i.e., by evaluating the geographic variation of the attribute in terms of what is commonly known as the "variogram" or "autocorrelation". New values of the attribute are thus obtained by computing a weighted average of the known values of the attribute in the neighbourhood according to an equation of the kind $\tilde{E}c_0 = \sum_{i=1}^{N} \lambda_i \tilde{E}c_i$, where $\tilde{E}c_i$ is the predicted value at the ith location, λ_i is the weight attributed to the predicted value at the ith location, and c_0 is the prediction location (see, e.g., Waller and Gotway 2004). How to compute the joint predicted values $\tilde{E}c_i$ and how to define the weight depends on the kriging technique; in this study, in particular, we used the Empirical Bayesian Kriging (EBK) technique, which is the main one used and, with respect to other alternative kriging techniques, enables a continuous representation of the data by predicting values in a spatial term between sample points where observations are not available. In fact, the values of AEC_R obtained through the EBK allow identifying the transmission of the infection in the different geographical areas on a larger scale than the municipal one due to their geographical location and proximity to other areas with a high rate of infection. On the contrary, for each specific municipality, the difference between the observed value of AEC_R and the predicted one through EBK highlights the singularity of the municipality with respect to its proximity, thus providing information on a small scale. For this reason, the relative difference index RDc defined as $RDc = \left(Ec - \tilde{E}c\right)/\tilde{E}c$ has been computed for each municipality c, where Ec is the observed AEC_R while $\tilde{E}c$ is predicted AEC_R through EBK. Note that the difference has been further divided by the predicted value to let comparable the differences where real AEC_R are not comparable. Thus, the relative difference index provides a measure of AEC_R with respect to the nearby cities, and for this reason, it has been used to group the municipalities in those having "high relative AEC_R" (the 25% having the higher RDc) and those having "low relative AEC_R "(the 25% having the lower RDc, which result to be negative in most of these cases). A statistical analysis of the characteristics of the two groups, in terms of indicators associated with each city, has been finally developed; graphical representations of the distributions of such indexes and suitable statistical test to compare the two groups have been performed.

The three indicators used in this statistical analysis, for which comparisons among the two groups have been performed, are the population density (D_p), the ageing index (I_a), and the annual average traffic flow ($AADT$). D_p is calculated simply by dividing the population of each municipality by the total area of each city (km2) (2021). The I_a is a dynamic statistical indicator used in demographic statistics to describe the weight of the elderly population in each population and is measured by dividing the number of inhabitants equal or more than 65 years by the population who have equal or less than 14 years. Finally, the $AADT$ represents the total volume of highway or road vehicle traffic for a year divided by 365 days. Table 2.1 presents the description of all four indicators, how they are calculated, and their data resource.

Table 2.1 Table of indicators

Indicator	Definition	Formula	Variables	Unit	Resource of data
Exposure to COVID-19 contagion (annual indicator)	The number of positive cases in each municipality relative to its population and calculated as an annual average	$AEC_R = \frac{\sum_i p_i}{I \times 365}$ $i = 1, 2, \ldots 365$	$AEC_R =$ level of exposure $P_i =$ number of positive cases in each day of the year $I =$ inhabitants of the municipality	n	The data regarding the daily positive cases are extracted from the official website of Piedmont Region. https://www.regione.piemonte.it/web/covid-19-mappa-piemonte
Population density	Measurement of population per unit area	$D_p = \frac{N}{A}$	$D_p =$ population density, $N =$ the total population $A =$ the land area covered by the population	n./ square metre	Population data are extracted from The Italian National Institute of Statistics (I.Stat) on 1 January 2021. http://dati.istat.it/Index.aspx?lang=en&SubSessionId=5585f6f0-9527-4c1d-8b05-666cf0882d59# The land area covered by the population is extracted from The Italian National Institute of Statistics. https://www.istat.it/it/archivio/156224
Ageing index	A dynamic statistical indicator used in demographic statistics to describe the weight of the elderly population in each population	$I_a = \frac{P_a \geq 65}{P_a \leq 14}$	$I_a =$ ageing index $P_a =$ population age	n./n	Population data are extracted from The Italian National Institute of Statistics (I.Stat) on 1 January 2021. http://dati.istat.it/Index.aspx?lang=en&SubSessionId=5585f6f0-9527-4c1d-8b05-666cf0882d59#

(continued)

Table 2.1 (continued)

Indicator	Definition	Formula	Variables	Unit	Resource of data
Annual average daily traffic	The total volume of vehicle traffic of a highway or road for a year divided by 365 days	$AADT = \frac{1}{n}\sum_{k=1}^{n} VOL_K$	AADT = annual average daily traffic VOL_k = daily traffic on kth day of the year n = number of days in a year (365 or 366)	n./year	Rapporti sulla Mobilità Veicolare in Piemonte: https://www.regione.piemonte.it/web/temi/mobilita-trasporti/sistema-informativo-regionale-dei-trasporti/rapporti-sulla-mobilita-veicolare-piemonte

For each year, the distributions of the indicators of population density (D_p), *ageing index* (I_a), and annual average daily traffic ($AADT$) in the two groups of "high relative contagion (AEC_R)" and "low relative contagion (AEC_R)" cities have been compared to verify if there are statistically significant differences between such groups in terms of the characteristics of density, population age, and intensity of traffic of the corresponding municipalities.

2.3 Results and Discussions

As mentioned earlier, this study first analyses the contagion territorial changes and outbreak movements within the whole Piedmont Region. Subsequently, we analyse the municipalities which unexpectedly have higher or lower contagion by statistically testing three territorial indicators, including population density, ageing index, and annual average traffic flow.

The mapping of contagion over time is useful to identify and locate the hot spots of the outbreaks and to understand how the outbreak moves within the territory. In addition, it can be evaluated how the mitigation and recovery measures are affecting the territory.

As can be seen in Fig. 2.3, the first outbreak is associated with high relative contagion in the eastern territories bordering Lombardy and Emilia-Romagna Regions, where the first clusters of positive cases were found. During July and August, a significant reduction in the number of positive cases led to the absence of significant hot spots or cold spots. Unlike the first outbreak, the routes for spreading during the second outbreak originate from the southern regions of Liguria and the French Provence-Alpes-Côte d'Azur. This might be due to the mass movements of the people to the coastal regions during the summer. The third outbreak started with clusters of hot spots in the province of Torino, and until May 2021, it continued spreading and reached the southern regions. Again in the second year, during July and August

2021, a significant reduction has been noticed like the first year, and once more, the last analysed outbreak originated from the cluster of hot spots close to the southern municipalities bordering Liguria. In addition, unless the first outbreak, the eastern regions were most of the time among the cold spots, which might be due to the regional lockdowns put into place. This pattern can also be seen if the annual maps of the first and second 12 months are compared.

In addition to the analysis of changes in the contagion pattern within the territories, the scale of our analysis also allowed to take a closer look to the situation of particular municipalities as well. In more detail, although analysing the hot spots and cold spots helps to understand how the outbreaks move within the territories, there are some

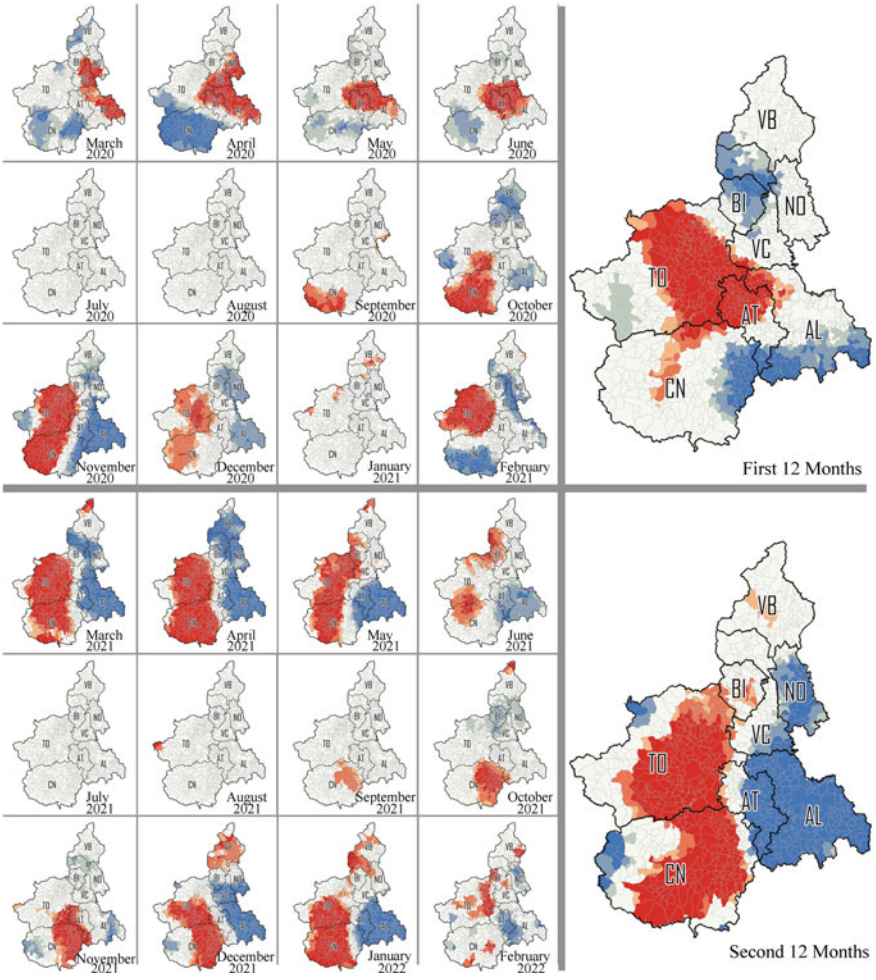


Fig. 2.3 Hot spot analysis of the COVID-19 contagion in the Piedmont Region (monthly maps are presented on the left and the annual maps are presented on the right)

municipalities that—despite being within the same cluster of hot spots or cold spots—show a significant difference in terms of contagion level regarding the neighbours. These municipalities might show either an unexpectedly higher or lower contagion. In the following phase of the study, we aim to verify if this difference is related to some territorial variables by statistically testing the relationship between the contagion and three indicators: Population density, annual average traffic flow, and ageing index.

In order to analyse the territorial characteristics of the municipalities with unexpectedly higher or lower contagion, it is first necessary to locate these municipalities. To this aim, as can be seen in Figs. 2.4 and 2.5, two maps are created and compared. The map on the left shows the level of COVID-19 contagion for each municipality using the real data. The map on the right is created using the EBK in which the value for each location on the map is affected by the nearby locations and this leads to the creation of a continuous map in comparison to the previous map which was more discrete. By using the EBK technique for each municipality, a new value is predicted based on the surrounding values, which represents the contagion considering the geographical context. Then this predicted value for each municipality is extracted using the EBK. Subsequently, this value is compared to the previous map, which represents the actual value of the contagion for 1000 inhabitants. Accordingly, the municipalities with relatively high or relatively low differences between the actual and predicted values are found. Afterwards, the higher and lower quartiles are extracted. The importance of these municipalities comes from the fact that, regarding their geographical location, their contagion rate is unexpectedly high or low, and the reason behind this fact is worth studying.

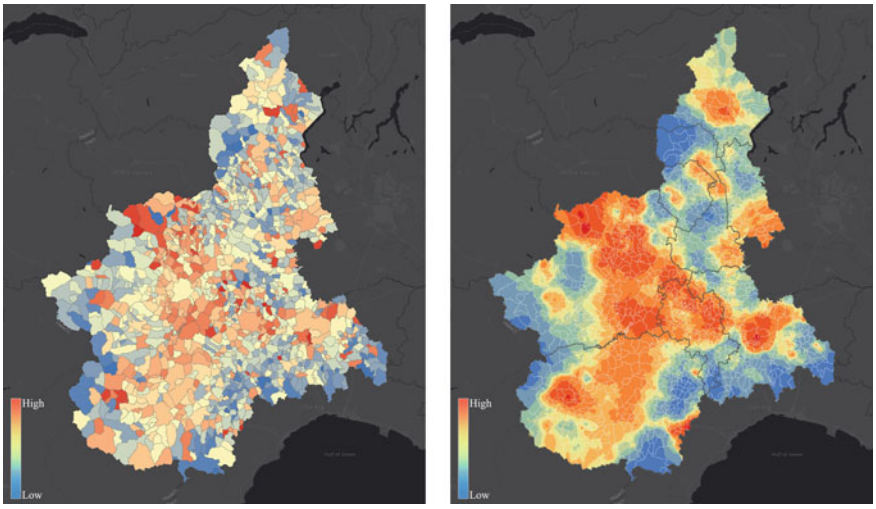


Fig. 2.4 Geographical exposure to COVID-19 contagion during the first 12 months of the pandemic using actual data (left) and EBK technique (right)—These two maps are compared to find the unexpectedly high or low value municipalities

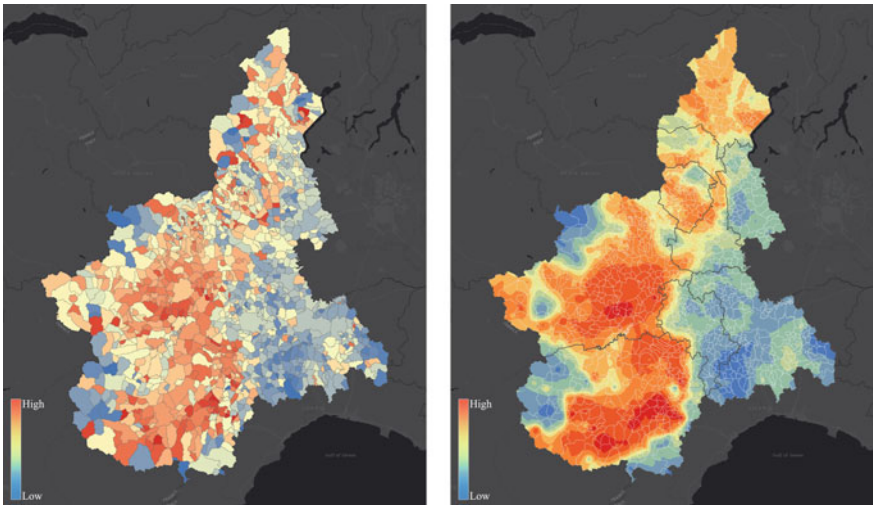


Fig. 2.5 Geographical exposure to COVID-19 contagion during the second 12 months of the pandemic using actual data (left) and EBK technique (right)—These two maps are compared to find the unexpectedly high or low value municipalities

The same procedure is also done for the data of the second 12 months of the pandemic. The actual value and EBK maps are presented in Fig. 2.5.

In addition to the AEC_R values, the territorial indicators, including D_p, I_a, and $AADT$ are also spatialised in correlation with the indicator of COVID-19 contagion, which are presented in Fig. 2.6. These maps are created using a multivariate visualization technique available in ArcGIS. The variations in the colour always represent different levels of COVID-19 contagion for the whole period of 24 months in different municipalities, while the dimension of the symbols refers to each of the three indicators. These maps are created to give an overview of the correlation between the spatial distribution of COVID-19 contagion and the spatial distribution of each indicator. It can be seen from the maps that the pattern of distribution for population density and the annual average of the daily traffic flow show a concentration of red colour big symbol size in the central zones, which suggest that high number of contagions overlaps high values for population density and traffic flow in these zones. However, this correlation is not observed for ageing index. Each of these relations will be separately tested using a set of statistical techniques to uncover their relation in the following paragraphs.

The statistical analyses are aimed at investigating the characteristics (expressed through the indicators of density, ageing, and daily traffic) of the municipalities that have very high relative AEC_R difference index (therefore with very high AEC_R compared to proximity) or very low (very negative, therefore with very low AEC_R compared to proximity). This has been done by comparing the distributions of the indicators in the two groups. The analysis has been repeated twice, once for each year of observation.

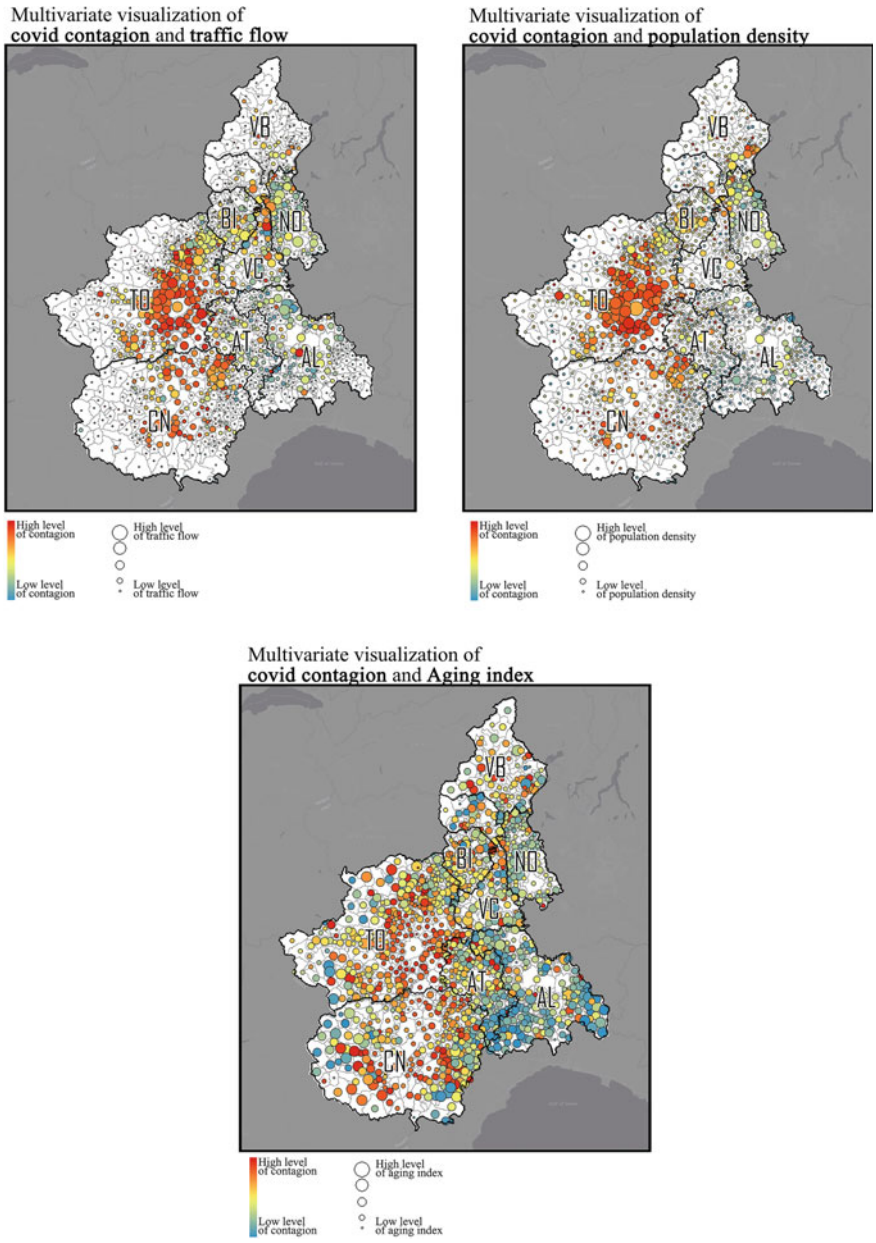


Fig. 2.6 Multivariate visualization of the COVID-19 contagion and the three spatial indicators: annual average of the daily traffic flow (top-left), population density (top-right), and ageing index (bottom)

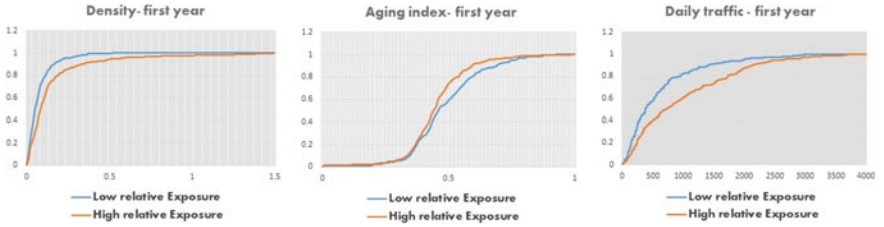


Fig. 2.7 Graphical representations of the cumulative distributions of each indicator for the municipalities with low/high relative exposure difference index during the first year of the pandemic

For the first year (March 2020–February 2021), the graphical representations of the cumulative distributions are those shown in Fig. 2.7, where the red line refers to high relative AEC_R municipalities, while the blue line refers to low relative AEC_R municipalities.

As one can see from Fig. 2.7, for all three indicators, the two distributions are stochastically ordered, i.e., they do not cross each other. This means that, for any value of the indicator, the percentage of municipalities having AEC_R smaller than such a value is always higher for the same one of the two groups. For the D_p, given any value d, the percentage of municipalities having D_p smaller than d is higher in the low relative AEC_R, (blue line) which means that this group has more "lower D_p" municipalities than the high relative AEC_R group (red line). The same happens for what concerns $AADT$, while the opposite is verified for the I_a.

A two independent samples test having equality of distributions as a null hypothesis has been performed to understand better if a testing procedure statistically confirms this graphical result. In particular, since the normality of these distributions is clearly not satisfied, the non-parametric Mann–Whitney U test has been applied (see, e.g., Fay and Proschan 2010), obtaining the p-values described in Table 2.2.

Table 2.2 Whitney U test results regarding the three territorial indicators for two groups of cities with high and low exposure during the first year of the pandemic

Mann–Whitney U test for independent samples—First year				
Indicator	Group	Mean	St. error of mean	P-value for the hypothesis of same distribution
Density index	Low relative exposure	0.071	0.004	0.00
	High relative exposure	0.163	0.017	
Ageing index	Low relative exposure	0.486	0.009	0.04
	High relative exposure	0.453	0.008	
Daily traffic index	Low relative exposure	314	21.6	0.00
	High relative exposure	501	26.8	

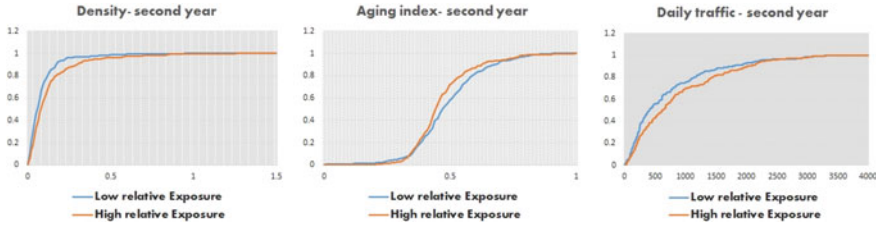


Fig. 2.8 Graphical representations of the cumulative distributions of each indicator for the municipalities with low/high relative exposure difference index during the second year of the pandemic

Equality of the distributions is strongly rejected in all three cases. One can thus affirm that municipalities in the low relative AEC_R group have, in distribution, lower D_p, low $AADT$ and higher I_a in the population.

For the second year (March 2021–February 2022), the graphical representations of the cumulative distributions are those shown in Fig. 2.8. The same results for the first year are obtained, even if the distances among curves are now smaller.

The results for the Mann–Whitney U test having equality of distributions are shown in Table 2.3. Again, the hypothesis can be strongly rejected, except for what concerns the I_a for which the p-value is greater than 0.1.

The results of the overmentioned analysis are in line with the hypothesis originating from mapping results, especially for the first year. It is demonstrated that the municipalities with an unexpectedly higher rate of infection than the nearby cities during the first year are more likely to have more D_p, more $AADT$ and less I_a. For the second year, two main differences are observed. The first relates to the I_a where its correlation with high exposure to the COVID-19 transmission could not be verified anymore. Secondly, for D_p, and $AADT$, the curves representing the difference between the two groups are closer to each other. These results suggest that in the

Table 2.3 Whitney U test results regarding the three territorial indicators for two groups of cities with high and low exposure during the second year of the pandemic

Mann–Whitney U test for independent samples—second year				
Indicator	Group	Mean	St. error of mean	P-value for the hypothesis of same distribution
Density index	Low relative exposure	0.081	0.006	0.00
	High relative exposure	0.122	0.008	
Ageing index	Low relative exposure	0.484	0.008	0.11
	High relative exposure	0.467	0.007	
Daily traffic index	Low relative exposure	349	21.8	0.01
	High relative exposure	448	25.6	

beginning phase of the pandemic, the impact of these two territorial variables is more significant and is more important to be considered.

2.4 Lessons Learned from COVID-19. The Leading Role of Spatial Dimension

It has been over two years since COVID-19 became a pandemic, and its behaviour is still unclear despite the health emergency ends. What is increasingly evident is that the spatial aspect of the pandemic is instead the central issue in understating the disease distribution patterns over territories. Although COVID-19 is full of unknowns, the spatial analysis assumes a leading role in interpreting the pandemic and its impact on decision-making and everyday life.

By mapping the spatial dynamics of COVID-19 transmission in the Piedmont Region through a GIS-based geostatistical analysis, this chapter initially showed that the outbreaks spread in the territories with different patterns of movements over time. These patterns are likely to be related to the implemented policies in place during the pandemic. For example, this study shows that although the first outbreak originated from hot spots of contagion in the western municipalities bordering regions of Lombardy and Emilia Romagna, during the rest of the pandemic, these municipalities turned to cold spots, probably because of the regional lockdown measures. The two annual maps to track the movement of the disease outbreaks over time performing a GIS-based hot spot analysis show how and where municipalities with either high or low values of contagion cluster spatially. In other words, to be a statistically significant hot spot, a feature must have a high value and be surrounded by additional features with high values. The hot spot analysis—performed in different periods—helped us to clarify the territorial pattern of the outbreaks during the pandemic and clarifies how the existing policies and measures affected the situation. Although proper, hot spot analysis only tells us some things about spatial contagion differences. Many times, within a cluster of municipalities which shape a hot spot (or cold spot), there are single municipalities which show a significant difference from the rest of the municipalities in the cluster. An example is shown in Fig. 2.9, which represents the data for the second 12 months of the pandemic in two different maps. The first map on the left represents a hot spot analysis. And the second one shows the heat map of the number of contagions for 1000 inhabitants in each municipality. As seen from the map on the right, some municipalities, despite being located within clusters of hot spots or cold spots, significantly differ from the nearby municipalities.

Accordingly, after performing the hot spot analysis, this study applied the Empirical Bayesian Kriging (EBK) to find and geographically locate the municipalities which show an unexpectedly high or low contagion compared to the surrounding. We found out that some municipalities—even if they shape a cluster of hot spots or cold spots with their neighbours—have unexpectedly higher or lower values of contagion regarding the nearby cities. Therefore, these municipalities were detected

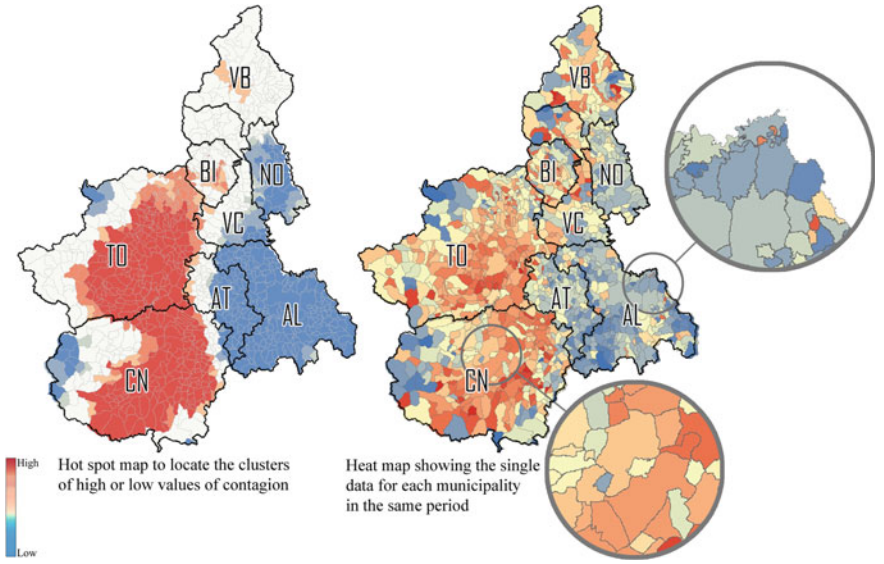


Fig. 2.9 Second year contagion map in the Piedmont Region (hot spot map on the left, and the number of positive cases for 1000 inhabitant for each municipality on the right)

using the EBK technique, and a statistical test was performed to investigate their territorial characteristics. Three indicators were explored for these municipalities. It has been found that the municipalities with suddenly higher exposure to contagion are more likely to have more population density, more mean annual traffic flow, and less ageing index, especially during the first year. The same but a slighter correlation is verified for population density and traffic flow during the second year, while the impact of the ageing index in the second 12 months of the pandemic is not verified. In a nutshell, the spread is not "nonlinear".

Moving from the analysis to the policy side, the findings of this study have several potentially significant implications for policymaking. As became clear during these two years of COVID-19, the policy responses to pandemics have a territorial dimension. Although most policy responses are at the national level and with national coverage, they result in very different regional situations once restrictive measures have been put in place. Some regions and municipalities faced more intense and/or longer-lasting consequences than others. More detailed, the current safety measures in Italy are merely planned and imposed based on the administrative borders of the regions and/or municipalities without considering the spatial variations of the phenomenon within territories. A comprehensive revision in the safety measures according to these characteristics may be helpful to cope with similar future scenarios towards more efficient actions based on real-time data and territorial analysis. For example, stricter regulation of activities and movements in areas with high levels of connectivity may be more effective at slowing the spread of COVID-19 than focusing on limiting movement everywhere. In addition, the temporal analysis shows that the

hot spots and cold spots of COVID-19 contagion move over time, so future safety measures must consider the time scale to determine when and where to interfere with mitigating the impacts and enhancing territorial resilience. This issue becomes more significant considering the importance of anticipation and early action in case of such a phenomenon.

A limitation of this study regards the fact that here we analysed the spatial dimension of the pandemic considering the exposure of territories to the spread of the disease. A further study could also assess the vulnerability of the population to the phenomenon—as counterpoised to transformative resilience—so that a more comprehensive understanding is given, which directs us to analyse the territorial resilience of the studied area (Brunetta et al. 2019). From this perspective, it is pretty shared among urban scholars that the COVID-19 pandemic can become a catalyst for urban change (Zgórska et al. 2021) by supporting solutions that would not take room during different times.

Overcoming this streamlined perspective, this chapter proposes to move towards a territorial approach to pandemics aimed at tackling the challenges regarding territorial vulnerabilities, fostering the coping capacity of the territorial systems as a whole in a transformative resilience perspective. In this line, transformative resilience implies a "build back better" approach, providing the ability to cross thresholds and move territorial systems into new basins of attractions following emergent and often unknown development trajectories.

2.5 Contributions

The article has been read and approved jointly by the four authors. In particular, Ombretta Caldarice authors the final version of the paragraph 1, Franco Pellerey authors the final version of the paragraph 2, Danial Mohabat Doost authors the final version of the paragraph 3, Grazia Brunetta authors the final version of the paragraph 4.

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