Beyond density: COVID-19 as an accelerator of spatial (in)justices

Habitat International 143 (2024) 102975

Contents lists available at ScienceDirect

Habitat International

journal homepage: www.elsevier.com/locate/habitatint

Beyond density: COVID-19 as an accelerator of spatial (in)justices

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ARTICLE INFO

Keywords:
Covid-19
Population density
Socio-spatial inequalities
Spatial justice
Comparative urbanism
Quantitative models

ABSTRACT

Around the end of 2019, in Wuhan, Hubei Province, China, the first confirmed cases of COVID-19 were identified, and from then on, the world we were used to knowing changed globally. The role of population density, in relation to the spread of the pandemic, has been widely scrutinised in urban studies, believed to be *the* triggering variable. However, the results so far are inconclusive. This paper suggests instead to shift the focus to socio-spatial vulnerabilities, as the effects of the pandemic's spread have been more severe in urban units which feature long-standing inequalities. The paper's aim is, therefore, twofold: on the one hand it aims at contributing to the debate on population density and COVID-19 in urban areas, and, on the other hand, to analyse the pandemic's spread in relation to socio-spatial vulnerabilities. Different cities across the globe are drawn into a comparative project, where the pandemic's spread is analysed in relation to variables of Population Density (PD) and a Social Vulnerability Index (SVI), by employing correlation matrices. The results suggest that there is no significant correlation between density and the spread of COVID-19. Instead, a positive correlation is in place when analysing the pandemic's diffusion with socio-spatial inequalities.

1. Introduction

The first confirmed cases of COVID-19 were discovered towards the end of 2019, and the world as we knew it began to alter. The pandemic captured the interest of many researchers in a variety of research fields. Besides the focus on medical studies, a great deal of research has linked the dynamics of the pandemic to cities and how they responded, bringing back the debate on their potential vulnerabilities (Wade, 2020). The research carried out in the past years has shown that the impact of the pandemic has not been homogeneous throughout cities (Biswas, 2020; Duggal, 2020; Kihato & Landau, 2020), thus fostering the debate on the possible socio-spatial determinant connected to COVID-19 cases. On the one hand, a great deal of studies has focused on density as the main contributor to the spread (e.g., Boterman, 2020; Hamidi, Sabouri, & Ewing, 2020; Lin et al., 2020). However, as shown by Sharifi and Khavarian-Garmsir (2020) the results are inconclusive and there is still unclarity on the actual relationship between high population density and the higher propagation of COVID-19. On the other hand, another stream of literature has focused on the dynamics of the pandemic in relation to long-standing structural inequalities, suggesting that a positive correlation is in place. This study aims at contributing to both debates, digging into the variables that correlate with the pandemic's spread. To do so, the research focuses on two aspects.

Firstly, it investigates the discrepancies of COVID-19 cases at a granular scale. Most of the research carried out so far, indeed, focuses on the city scale or above. Thus, any information about the intra-city differences in spread do not emerge. This gap is intended to be filled by retrieving data concerning the pandemic's spread at the lowest possible scale, correlating it with Population Density (PD) and a Social Vulnerability Index (SVI). Notably, the paper presents descriptive information on the relationship between density, socio-spatial vulnerabilities, and pandemic transmission, but does not mean to establish a plausible causal association, nor does it examine the outbreak's timeframe.

Secondly, it works towards a comparative approach that spans across different contexts; drawing comparisons across predefined categories, such as Global South and Global North, to build more robust findings and to question the results from different perspectives. In a nutshell, the paper aims to address the following research questions.

- What kind of relationship is in place between population density and the spread of COVID-19 when carrying out intra-city analyses?
- Is the pandemic's spread positively correlated with existing structural socio-spatial inequalities within cities?

The work is structured in six parts. After this introduction, the second section summarizes the main research carried out on COVID-19 and cities, with a focus on studies investigating the role of density and socio-spatial inequalities in relation to the spread of the pandemic. The third

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https://doi.org/10.1016/j.habitatint.2023.102975
Received 29 April 2023; Received in revised form 14 November 2023; Accepted 16 November 2023
Available online 8 December 2023

segment presents the methodology and methods employed by this study. The fourth part details the data used to carry out the analyses. The fifth section shows the results of the investigations. Finally, the sixth part discusses the main findings and summarizes the main features of this work.

2. Background: COVID-19, population density and socio-spatial inequalities

2.1. Higher population density does not necessarily rhyme with higher spreads

Existing literature has primarily focused on density-related factors while other urban planning-related elements (such as the proximity to services) are still relatively understudied, although some works explored these aspects (e.g., Kawlra & Sakamoto, 2021). The COVID-19 outbreak brought to light issues concerning the desirability of compact urban development. Due to the high level of face-to-face interaction, densely inhabited and well-connected places were thought to be hotspots for the rapid spread of the pandemic. However, the evidence for a link between density and COVID-19 is still contradictory.

On the one hand, in the Netherlands, Boterman (2020) employed correlation and regression models and found no significant positive link between county density and infection rate, despite the country being heavily urbanised and densely inhabited. Similarly, Lin et al. (2020) using regression models discovered that the percentage of the people that came from Wuhan, as well as population density, are critical elements that can explain the COVID-19 dissemination rate in China. However, once the former variable was controlled for, the linear relationship between population density and spread rate vanished. Thus, they investigated the effect of population density further and discovered that high spread rates do not exist in densely populated metropolitan areas. In congruence with these findings, but carrying out a sub-city level of analysis, Khavarian-Garmsir, Sharifi, and Moradpour (2021) discovered that density alone cannot be regarded as a risk factor for the spread of COVID-19, based on data examined using structural equation modelling. Indeed, the geographic distribution pattern of confirmed COVID-19 cases across Tehran's 22 municipal districts was not linked to population density. Finally, tying up this side of the debate, the systematic review produced by Zhang et al. (2022) evaluated and synthesised information from 21 studies on the associations between the spread of respiratory viruses (such as COVID-19) and population density, finding no consistent evidence of a positive relationship between these two factors.

On the other hand, other studies found that there is a significant link between density and the propagation of the virus. In two early stages of the pandemic in China (first phase: January 19 to February 1, second phase: February 2 to February 29), Qiu, Chen, and Shi (2020) investigated the effects of specific socioeconomic and environmental variables on transmission rates through a set of OLS regression models. While population density did not have a significant association with COVID-19 transmission rate in the first phase, it did have a substantial negative influence in the second phase, according to their findings. They stated that public health initiatives and the sharing of inter-city resources are two probable reasons for the second phase's reduced social interactions and the establishment of a substantial relationship. In congruence with these findings, Ren et al. (2020) by employing ecological niche models (ENM) found that in Beijing and Guangzhou, the highly high-risk zones of COVID-19 infection were likely to be in locations with higher population densities. Similarly, research on several Italian areas carried out through a multiple linear regression model found that regions with larger population densities have higher transmission rates (Cartenì, Di Francesco, & Martino, 2020).

The inconclusive nature of the results obtained so far can be linked to several reasons, which represent challenges also for this work. Firstly, population densities are not assigned at random, and they could be influenced by unobserved confounding factors. For example, locational productive advantages, whether natural or man-made, can influence population densities, affecting both local economic conditions and densities at the same time. Unobservable locational advantages can complicate the influence of density on the spread of COVID-19 insofar as its incidence is affected by economic conditions. Secondly, variances in the start of the disease can lead to cross-sectional differences in the intensity of the outbreak at a particular moment in time. Thirdly, behavioural responses to the pandemic may be affected by density variations, which may alter the disease's spread. Finally, due to differences in local testing methods and capabilities, statistics on COVID-19 instances may be reported incorrectly.

All in all, the role of density in relation to the pandemic is still debated. Several aspects are at play in each study: the scale, the timeframe, the definition of what density is, and how it connects to the pandemic. Therefore, the different outcomes might derive from the intrinsic heterogeneity of the elements cited just above.

2.2. Where does COVID-19 stands on existing socio-spatial inequalities?

From a socio-spatial point of view, the focus of the research so far has mostly been oriented to the negative impacts of the pandemic. However, there are also studies demonstrating the socially positive activities that the crisis activated. As in the case of rental housing cooperatives in Melbourne, Australia and Choluteca, Honduras (Guity-Zapata, Stone, & Nygaard, 2023).

Several works have focused on the dynamics of the pandemic in relation to long-standing structural inequalities within cities. Some studies, particularly, have analysed current events in connection to similar events of the past. From a historical point of view, pandemics have affected cities unevenly, hitting severely minorities and inhabitant verging in poor conditions (Duggal, 2020). This is due to prior conditions of economic difficulty and limited access to services (Wade, 2020). The COVID-19 pandemic made these sedimented issues re-emerge, providing new insights, and drawing attention to long-standing issues within cities (Kihato & Landau, 2020).

Several works have been published demonstrating that vulnerable groups have been hit the most worldwide. The studies range from the effects in New York City, where Wade (2020) qualitatively notices how the death rate is higher amongst Black and Latino people, compared to Whites. This is partly due to the limited access to healthcare during the pandemic. Also Maroko, Nash, and Pavilonis (2020) in their ecological cross-sectional study examined the demographic and economic nature of spatial hot and cold spots of COVID-19 rates in New York City (and Chicago). They found that cold spots were associated with wealthier neighbourhoods, having higher educational attainment, higher proportions of non-Hispanic white residents, and more workers in managerial occupations. Contrarily, hot spots were found to be closely associated with neighbourhoods featuring lower rates of college graduates, higher proportions of people of colour and greater average household size. In Singapore, Zhu, Zhu, and Guo (2022) demonstrated that the number of infected migrant workers residing in dorms was 300 times higher than the number of infected local urban residents. This discrepancy was attributed to both the migrants' "vulnerable" status and the conditions that promoted the virus's widespread spread. In Sao Paulo, Ribeiro, Ribeiro, Veras, and de Castro (2021) explored the relationship between social inequalities in COVID-19 mortality. Using data from March to September 2020, they conducted a population-based study that included COVID-19 deaths among residents of Sao Paulo. Age-standardized mortality rates and unadjusted rate ratios (RRs) were estimated by race, sex, age group, district of residence, household crowding, educational attainment, income level, and percentage of households in subnormal areas in each district. The "Joinpoint" model was used to analyse mortality trends over time. The results suggest that all socioeconomic indicators showed a positive gradient, meaning that rising disparities were linked to higher death rates. Within cities in the

Global South, informal urban settlements have been a further object of interest, due to high density, lack of access to basic infrastructures and higher exposure to COVID-19 (Ogas-Mendez, Pei, & Isoda, 2022; Wirastri, Morrison, & Paine, 2023). The spread of the virus was found to be more difficult to contain within slums, due to the impossibility of effectively enforcing lockdowns and quarantine actions (Wasdani & Prasad, 2020). This undermined the effectiveness of "homestay" orders for controlling the virus' transmission, as it makes it difficult for a person to socially isolate oneself (Mishra, Gayen, & Haque, 2020). Similar issues have also been highlighted in other African and Brazilian cities (Kihato & Landau, 2020; (Oliveira and Arantes, 2020)). Moreover, adherence to "stay home" orders is also difficult due to unstable economic situations and the fact that many communities (such as those in Sub-Saharan Africa, for instance) depend on intimate social relationships for their survival (Finn & Kobayashi, 2020; Kihato & Landau, 2020). As a result, there are worries that inequality may not only make containment difficult but also lead to increased virus spread. Finally, the lack of access to essential services like clean water to comply with handwashing requirements and medical care (such as hospital beds) further aggravates the conditions in informal settlements (Biswas, 2020; Oliveira and Arantes, 2020).

Overall, the pandemic has once again brought to light socio-spatial fault lines and disparities, complicating efforts to prevent, respond to, and recover from pandemics. Although the production of scholarship on the theme is significant, there is still a lack of studies exploring socio-spatial inequalities at a granular scale, especially in comparative terms *within* and *between* different contexts.

3. Methodology: gauging the diversity of urban experience

3.1. Stretching across divides: COVID-19, vulnerability, density

The enormous research produced, as insightful as it is, has also shown inconsistent findings, possibly linked, among other things, to different methodological and theoretical frameworks of analysis. From this perspective, bringing together diverse cities within a common analytical framework can help expand our understanding of the pandemic and the crucial elements that might have played a role in fostering the spread of the outbreak.

However, what kind of comparative approach should be envisioned? Which instances should be interrogated? The field of urban studies, as claimed by Robinson (2011) has been biased in its analytical framework by clustering cities into, for instance, developed and developing, capitalist and socialist, thus hindering the potential for research across these categories. However, as "globalisation" has acquired increasing importance in the definition of urban phenomena in the last decade, also the interest in drawing comparisons across different cities has gained traction. Scholars are increasingly engaging in comparisons encompassing a variety of urban contexts to build theoretical insights (e.g., McCann and Ward, 2011; Roy & Ong, 2011).

Following this rationale, the four case studies - London (UK), New York City (USA), Rome (Italy) and Sao Paulo (Brazil) – were chosen for three main reasons. Firstly, they deployed different prevention and control measures during the pandemic, which can be factored in qualitatively while analysing the results. Secondly, the epidemic and endemic periods in the four cities nearly coincided, which helped working with consistent data. Finally, from a practical standpoint, they all had an appropriate database that had information on the distribution of COVID-19 at the sub-city level, enabling the examination of intra-city analyses.

From the methods point of view, the pandemic's spread is analysed in relation to two variables: Population Density (PD) and a Social Vulnerability Index (SVI), this latter created by the Centers for Disease Control[1]. A Pearson's correlation coefficient is used to measure the linear relationship between the independent and dependent variables. In general, the correlation coefficient is a number that represents how closely two variables are related to one another. The values can be interpreted as follows: 1 (perfectly negative correlation), meaning that the variables tend to move in opposite directions; 0 (no correlation), meaning that there is no relationship between the variables; and 1 (perfectly positive correlation), meaning that the variables tend to move in the same direction. In this work, the Pearson correlation coefficient, usually referred to as Pearson's r, is a statistical indicator of the linear relationship between two sets of data. It is essentially a normalized measurement of the covariance, with the result always falling between −1 and 1. It is the ratio between the covariance of two variables and the product of their standard deviations.

4. Data: a focus on intra-city COVID-19 spread

Three variables were employed in this study: COVID-19 case rates, Population Density and a Social Vulnerability Index.

I chose to focus on COVID-19 case rates since death and hospitalization rates are more influenced by individual health characteristics such as age and the existence of comorbidities (de Andrade, Pereira, Martins, Lima, & Portela, 2020; Giorgi Rossi et al., 2020; Jassat et al., 2021). In all instances, the "case rates", which are the number of cases per 100,000 residents, have been used to map and analyse the pandemic. These represent more comparable statistics, as different units across the cities, having diverse population sizes, can be comparatively analysed (Figs.1–4).

Population density was calculated, for each case study, as the ratio between the population estimates (retrieved from the local censuses) and the reference area unit (Inhabitants/area), calculated through the GIS software (Figs. 5–8).

Finally, the Social Vulnerability Index (SVI) is a well-known measure in health research, particularly in medical emergencies and disease mitigation planning (Flanagan, Hallisey, Adams, & Lavery, 2018). According to the CDC, social vulnerability refers to "*the extent to which certain social conditions, such as high poverty, crowded housing, or a community's minority status, may affect the community's ability to prevent suffering and financial loss in the event of a disaster*" (Centers for Disease Control and Prevention, 2020). The SVI relies on a comprehensive framework that encompasses four primary domains (Flanagan, Gregory, Hallisey, Heitgerd, & Lewis, 2011). The first domain is Socioeconomic Status, which delves into various socioeconomic factors such as income, poverty, employment, and education. It's essentially a measure of the economic well-being and educational attainment of the population under study. The second domain, Household Composition and

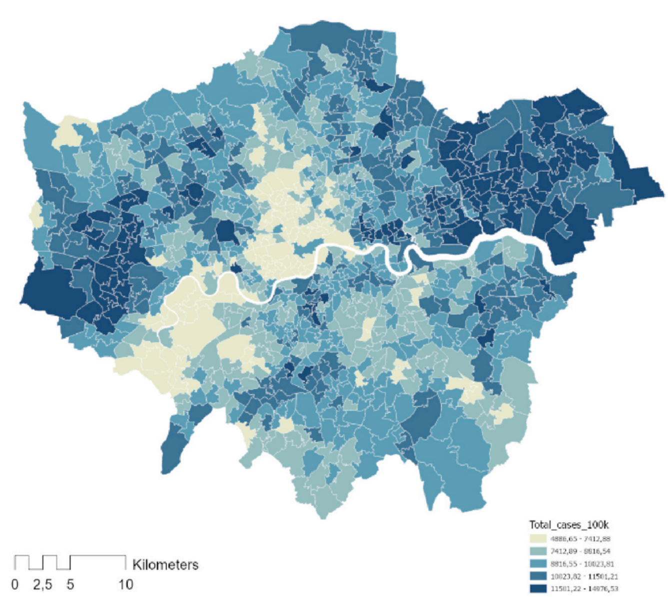

Fig. 1. London COVID-19 spread by MSOA.

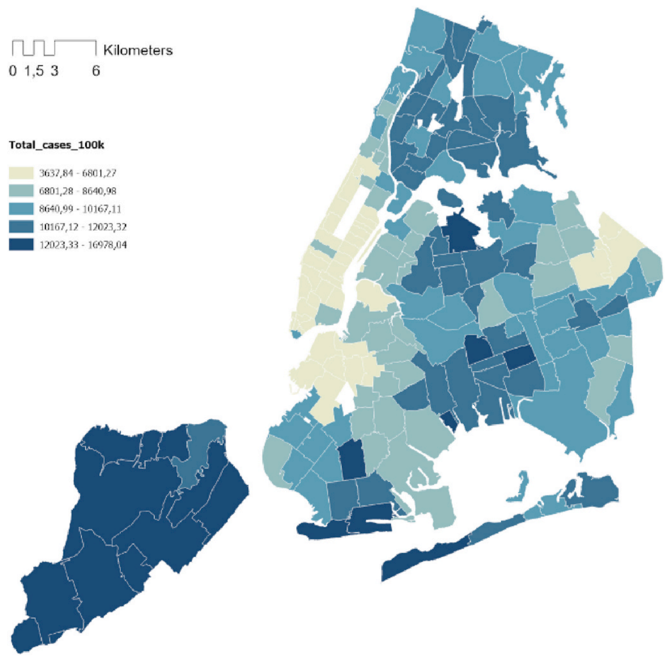

Fig. 2. NYC COVID-19 spread by MODZCTA.

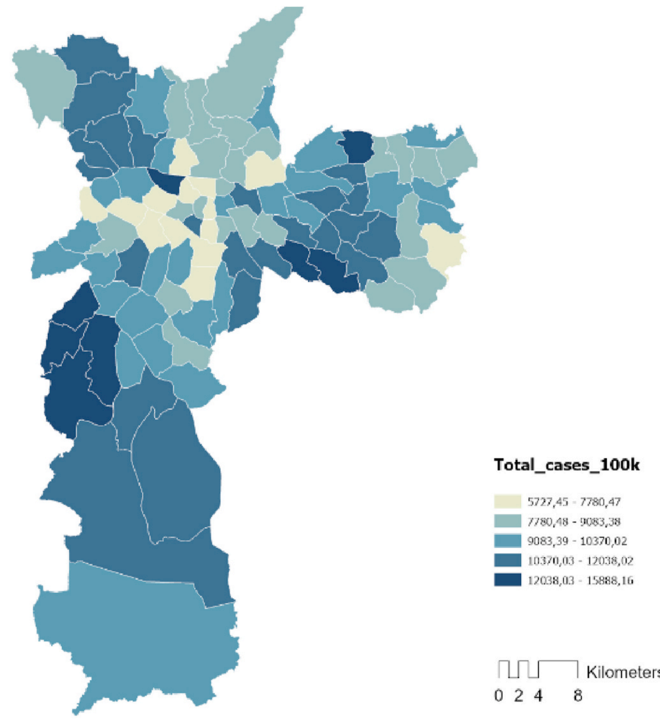

Fig. 4. Sao Paulo COVID-19 spread by District.

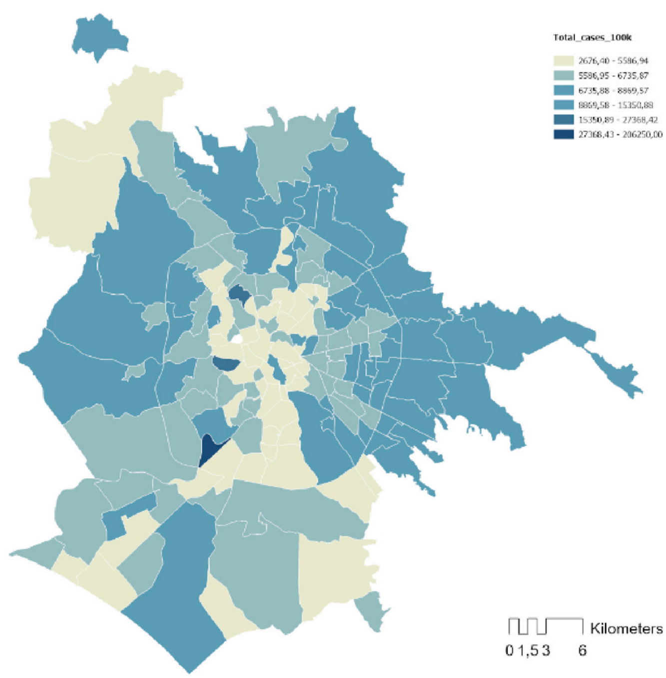

Fig. 3. Rome COVID-19 spread by ZUB.

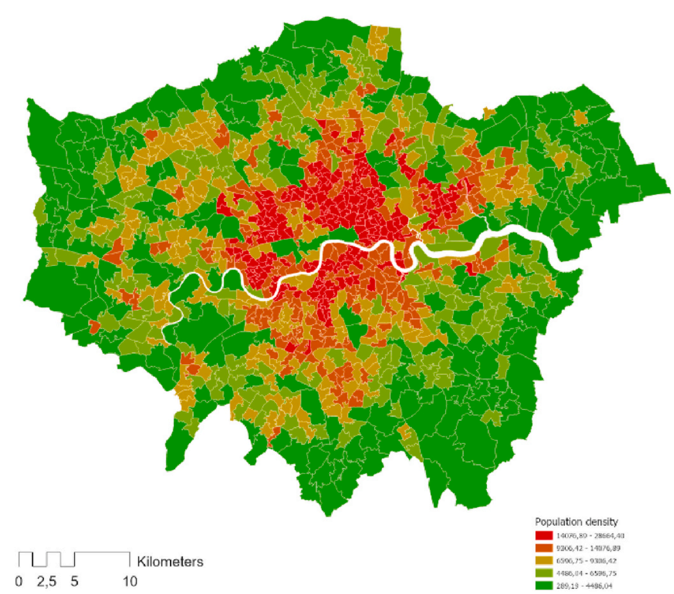

Fig. 5. London population density by MSOA.

Disability, considers demographic aspects. It includes variables related to age, single parenting, and disability. This domain helps in understanding the composition and unique challenges of households within the studied community. The third domain, Minority Status and Language, is concerned with the cultural and linguistic diversity within the community. It comprises variables associated with race, ethnicity, and language proficiency, providing insights into the multicultural aspects of the population. Lastly, the fourth domain, Housing and Transportation, offers insights into the living conditions and mobility of the community. It includes variables related to housing structure, crowding, and vehicle access, helping to assess the adequacy of housing and transportation resources available to the population. The variables employed to construct the Social Vulnerability Index (SVI) were ranked from highest to lowest across all spatial units, except for wealth variables which were ranked in the reverse order since, unlike the other variables, a higher wealth indicates lower vulnerability. To calculate the percentile rank for each spatial unit across these variables, the formula "Percentile Rank = (Rank-1)/(N-1)". Here, N represents the total number of data points, and any tied ranks were assigned the smallest corresponding rank. Furthermore, for each spatial unit, a percentile rank was computed for each of the four domains by summing the percentile ranks of the variables within each domain. Lastly, an overall percentile rank for each spatial unit was obtained by aggregating the percentile rankings from all four domains[2] (Figs. 9–12).

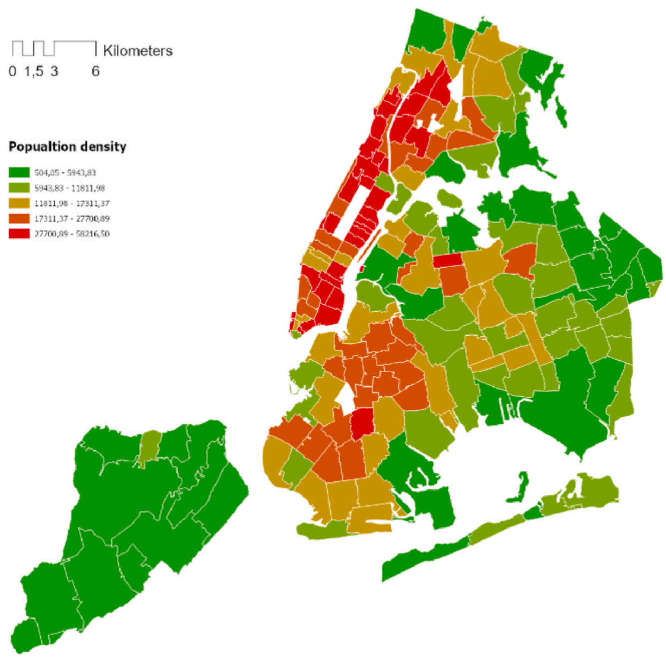

Fig. 6. NYC population density by MSOA.

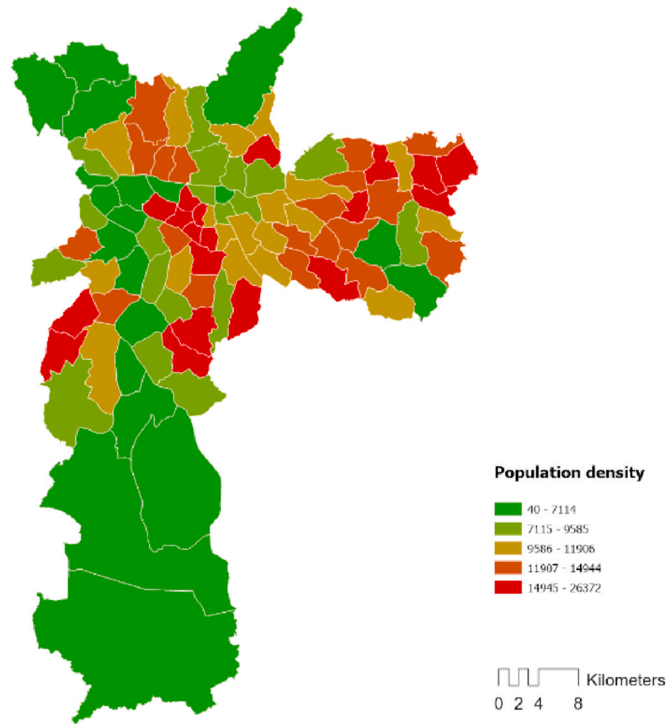

Fig. 8. Sao Paulo population density by District.

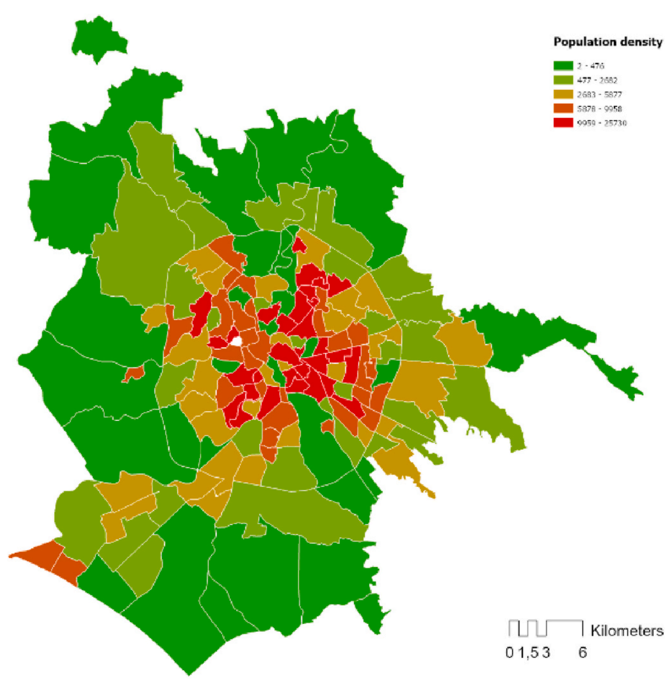

Fig. 7. Rome population density by ZUB.

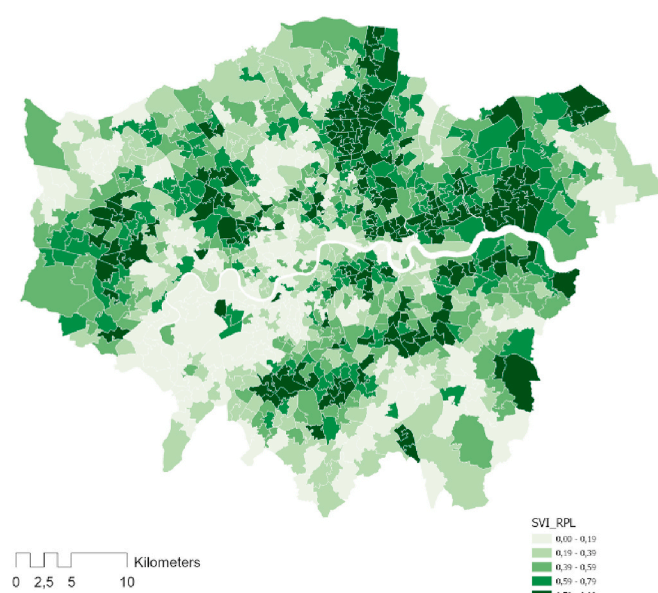

Fig. 9. London Social vulnerability index by MSOA

To test the robustness of the index across the different case studies, and to monitor its information content, the SVI was further correlated with the Life Expectancy (LE), which has been linked in the literature to health and social inequalities (Wood, Sutton, Clark, McKeon, & Bain, 2006; Bleich, Jarlenski, Bell, & LaVeist, 2012). Although this parameter was not provided for Rome (at the geographical scale of interest), for the other three case studies, the Person's correlation models between the two indices displayed moderate to strong negative correlations, with R values ranging from −0.6 to −0.97. This indicates that the two are indeed correlated and contain similar information, the sign is negative as, logically, the less vulnerable an area is, the greater the life expectancy, theoretically, is going to be. Therefore, using exclusively the SVI was considered to suffice for the purpose of this work. Whereas for NYC the index was already constructed, for the other case studies the index was not always provided, or existing, thus requiring the build-up of the index starting from the available variables and indicators.

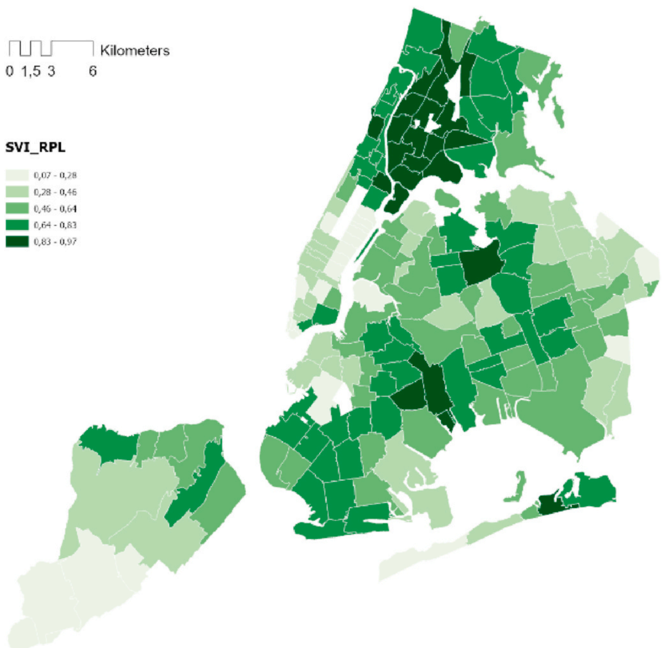

Fig. 10. NYC social vulnerability index by MSOA

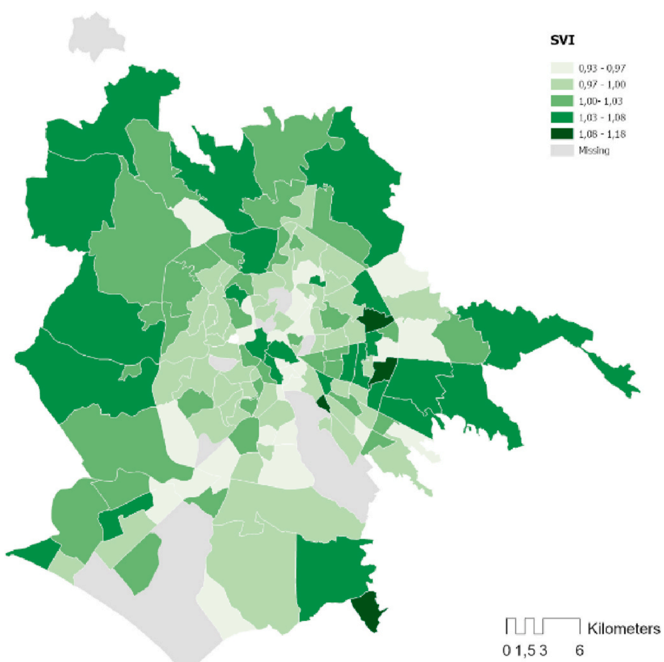

Fig. 11. Rome Social vulnerability index by ZUB

4.1. London

The COVID-19 data for London was obtained from the PHE (Public Health England) website and organized by Middle Layer Super Output Areas (MSOAs)[3]. The period of the data concerning the pandemic is from the March 29, 2020 until the July 25, 2021. The data was retrieved in the form of total incidence (tot. Number of cases per MSOA) and

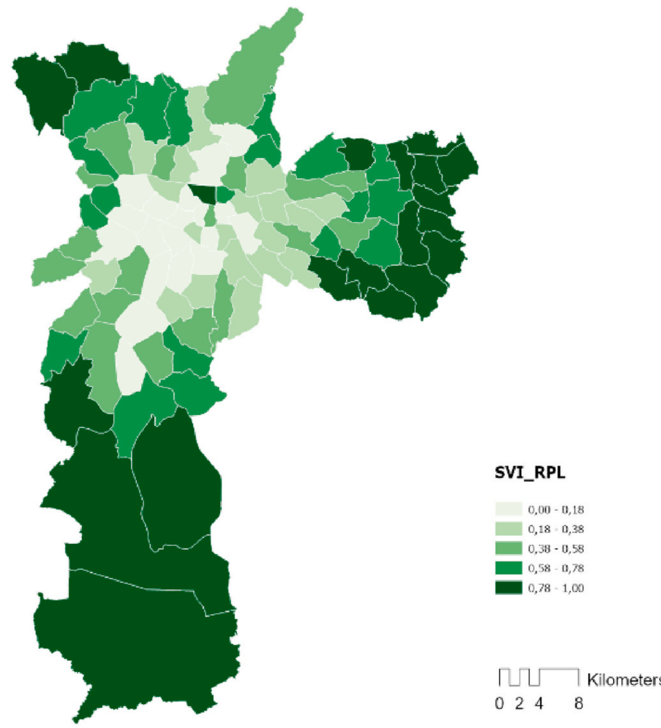

Fig. 12. Sao paulo social vulnerability index by district.

normalized per 100 k inhabitants dividing by the population estimates of the ONS in 2019 and then multiplied by 100.000. The population estimates were also used to calculate population density across MSOAs, by calculating the ratio between population and area.

In the case of London, to the author's knowledge, there was not an already constructed SVI[4]. Therefore, the SVI was built by retrieving similar variables to those used by the CDC and by applying the same methodology they proposed for the construction of the index. The singular variables and indicators were taken from the 2011 Census. Whenever possible, the variables have been taken as close to the CDC's as possible, also to maintain homogeneity across case studies. Some variables, instead, were not possible to retrieve[5].

4.2. New York City

For NYC, the data on COVID-19 was retrieved from the NYC DOHMH (NYC Department of Health and Mental Hygiene) GitHub open folder and organized according to MODZCTAs (Modified Zip Code Tabulation Areas) which was a spatial scale defined for the optimal calculation of rates across the city of New York. The time span is from the August 8, 2020 until the July 24, 2021. The data was already retrieved in the form of rate, calculated using interpolated intercensal population estimates. Population estimates were updated on November 9, 2020, to reflect annual population estimates for all New Yorkers as of July 1, 20,19[6]. Also in this case, the population estimates were used to calculate population density across MODZCTAs.

For NYC, as mentioned, the SVI was already constructed and rendered openly available by the CDC. The 2018 SVI data for NYC was provided at the census tract level[7]. To obtain the index for each MODZCTA, I averaged the SVI scores of census tracts that intersected each zip code.

4.3. Rome

COVID-19 data for Rome was provided by the DEP *Lazio* (Department of Epidemiology of the Regional Health Service - *Lazio*) already disaggregated according to the *Zone Urbanistiche* (ZUB) scale. In this case, however, the data was not openly available, and it has been provided upon official request to the DEP. The time span is from the 1st of March 2020 until the 29th of July 2021. The data was already retrieved in the form of rate, calculated using population estimates updated in 2020 provided by ISTAT (The Italian National Institute of Statistics) and prior to the COVID-19 outbreak. Again, the population estimates were used to calculate population density across ZUBs.

For Rome, the SVI was already constructed and named "*Indicatore di vulnerabilità sociale e materiale*"[8]. The SVI was constructed to express with a single value several aspects of social and material vulnerability of a territory. The index is constructed through the combination of seven elementary indicators describing the main "material" and "social" dimensions of vulnerability. The main dimensions that have been considered, based on the factors that can most determine a condition of vulnerability, are the following: the level of education, family structures, housing conditions, participation in the labour market and economic status[9]. The final values were already provided at the ZUB level for Rome. The index, as constructed by ISTAT, was thought to be suitable for the purpose of this research, as the variables and indicators used are close to the ones utilised by the CDC.

4.4. Sao Paulo

COVID-19 data in Sao Paulo was classified according to three different systems: *E*-SUS-VE Flu Syndrome (GS), Severe Acute Respiratory Syndrome (SRAG) and Deaths[10]. The first was taken to account for the spread of the pandemic in terms of cases. This was done to maintain homogeneity across different case studies and to avoid overlapping with SRAG (closer to hospitalization rates). The data was already disaggregated according to the Administrative Districts (*Distritos Administrativos*) scale. The time span is from the 1st of March 2020 until the 27th of July 2021. The data was retrieved in the form of absolute incidence; the rate was calculated using population estimates updated in 201,5[11], provided by *Fundação* SEADE (*The Fundação Sistema Estadual de Análise de Dados*). The absolute population estimates were used to calculate population density across districts.

Turning to the SVI, for Sao Paulo, *Fundação* SEADE created an index called "*Índice Paulista de Vulnerabilidade Social*" (Fundação SEADE, 2010), which would be equivalent to the SVI. Nevertheless, the specific variables and indicators used to construct it differ, to some extent, from the ones used for New York. For this reason, the index was reconstructed by retrieving the singular variables and indicators that were close to the CDC's SVI, following again their methodology[12].

4.5. Data description and summary of statistics: heterogeneity across case studies

Table 1, 2 and 3 summarize the data and the main statistics of the four case studies. As the title of the sub-paragraph suggests, there is a great deal of heterogeneity between the four cities.

The total population varies considerably, with Sao Paulo displaying the highest figure (11.581.798 inhabitants) and Rome having the lowest (2.808.293 inhabitants). NYC and London, instead, have similar statistics (8.336.817 and 8.961.989 inhabitants, respectively). Similarly, the total number of cases follows a similar distribution. Overall, Sao Paulo had the highest number of cases (1.157.079) and Rome was the least affected (176.479). Once again, NYC and London present similar figures (773.077 and 852.281 cases, respectively). However, by looking at the average case rate, it is possible to observe how in reality, by normalising the spread according to the population, the rates tend to be more aligned, with London, NYC and Sao Paulo displaying similar numbers (9.510, 9.273 and 9.990, respectively). Rome's average case rate is also close, although lower (6.284).

Population density, total area, number of areas and average area are all inextricably linked to one another. In terms of overall area, all cases range between 1.286 and 1.574 km^2, except for NYC, where the total surface is 757 km^2. Moreover, the total number of areas into which the surface is split (units/observations) significantly varies across the case studies. For London, the number of units is high (983 MSOAs), and the average area per unit, thus, is the lowest (1,6 km^2). In Rome and NYC, instead, although having a similar number of subdivisions (155 and 177 respectively), the average surface varies considerably (8 and 4 km^2 respectively) due to the difference in the total area. Finally, Sao Paulo displays the lowest number of units (96) and the highest average area (16 km^2), once again, due to the extensive overall surface of the municipality (1.528 km^2). As a result of the data described above, population density varies significantly across the instances. NYC shows the highest figure (17.279 inh/km^2), whereas Rome has the lowest (6.000 inh/km^2). Sao Paulo and London range in between (11.142 and 9.149 inh/km^2).

Tables 2 and 3 display the summary of statistics for both correlations. It is noticeable how the minimum and maximum values, as well as the mean, vary considerably between the different case studies when correlating PD with COVID-19, while the values for the SVI span across the index scale. Finally, it is noteworthy to point out how the standard deviation (STD), while similar in London, Rome, and Sao Paulo, is significantly higher in NYC (approximately doubled) when correlating PD with COVID-19. Differently, when analysing the relationship between the cases and the SVI, the STD ranges between 0,23 and 0,28 – except for Rome, where the figure is lower (0,04).

Table 2
Descriptive statistics - Population Density.

City	Observations	Min.	Max.	Mean	STD
London	983	289,11	28.653,29	9.145,70	5.417,82
NYC	177	504,06	58.216,51	17.279,24	12.220,55
Rome	155	2,44	25.729,72	6.000,09	5.966,17
Sao Paulo	96	39,81	26.372,15	11.141,81	5.233,49

Table 3
Descriptive statistics - SVI.

City	Observations	Min.	Max.	Mean	STD
London	983	0,00	0,99	0,49	0,28
NYC	177	0,07	0,97	0,57	0,23
Rome	144	0,93	1,18	1,00	0,04
Sao Paulo	96	0,00	1,00	0,50	0,29

Table 1
Case studies data description.

City	*Total cases*	*Total population*	*Total area (km^2)*	*N° of areas*	*Average area (km^2)*	*Average density*	*Average case rate*
London	852.281	8.961.989	1.574	983	1,6	9.149	9.510
NYC	773.077	8.336.817	757	177	4	17.279	9.273
Rome	176.479	2.808.293	1.286	155	8	6.000	6.284
Sao Paulo	1.157.079	11.581.798	1.528	96	16	11.142	9.990

5. Results: density and the role of socio-spatial inequalities

The results of the analyses are summarised in Table 4, Table 5 and Figs. 13–21.

Table 4 and Figs. 13–16 summarize the main statistics concerning the standardized coefficients obtained while correlating PD with COVID-19. It stands out how all coefficients present a negative value. Moreover, the magnitude of each is not significant (ranging from −0,12 to −0,08), except for the one related to NYC, where the value reaches −0,50, indicating a moderately significant negative correlation. For the other cases, instead, the values suggest no correlation.

The p-values (Pr > |t|) are close to zero for London and NYC, while for Rome and Sao Paulo the figures are higher (0,12 and 0,46 respectively), thus indicating a higher chance of encountering a null hypothesis. These results suggest that, on the one hand, the coefficients found for NYC and London are significant, given the lower standard deviations (0,07 and 0,03 respectively) and the low p-values (<0,05). On the other hand, the p-value for Rome and Sao Paulo indicates that the estimation made could vary more significantly. This might be due to greater

Table 4
Standardized coefficients – PD/COVID-19.

City	Value	STD	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
London	−0,12	0,03	−3,62	0,00	−0,18	−0,05
NYC	−0,50	0,07	−7,64	0,00	−0,63	−0,37
Rome	−0,12	0,08	−1,54	0,12	−0,28	0,03
Sao Paulo	−0,08	0,10	−0,74	0,46	−0,28	0,13

Table 5
Standardized coefficients – SVI/COVID-19.

City	Value	STD	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
London	0,51	0,03	18,45	0,00	0,45	0,56
NYC	0,43	0,07	6,27	0,00	0,29	0,56
Rome	0,30	0,08	3,59	0,00	0,13	0,45
Sao Paulo	0,25	0,10	2,41	0,01	0,04	0,44

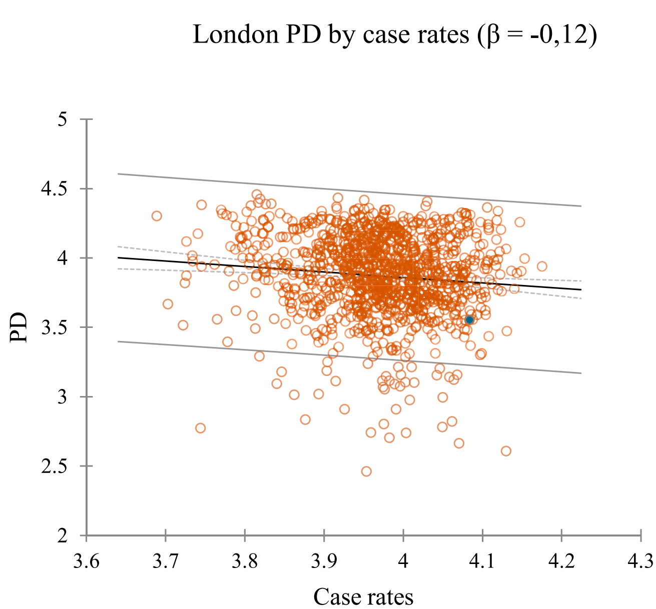

Fig. 13. Scatterplots and coefficients for the correlations between PD and case rates.

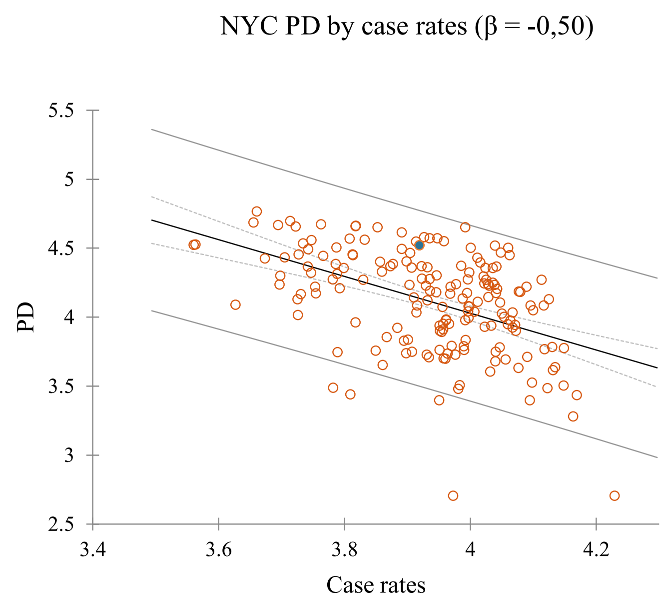

Fig. 14. Scatterplots and coefficients for the correlations between PD and case rates.

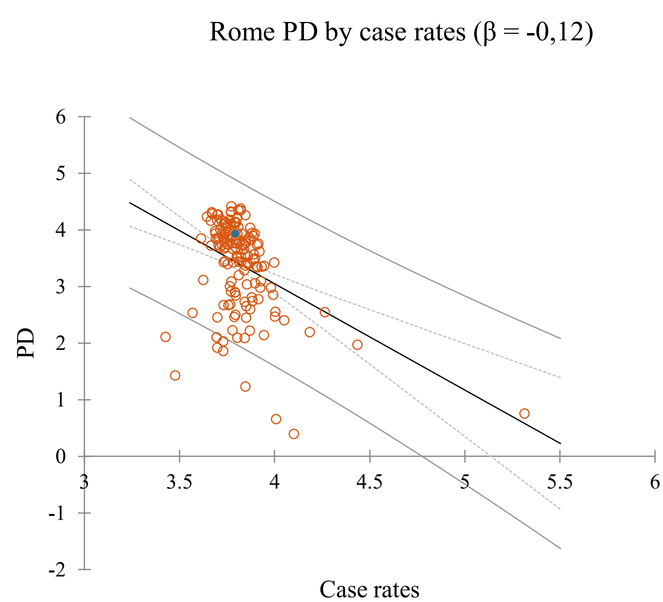

Fig. 15. Scatterplots and coefficients for the correlations between PD and case rates.

variations in the magnitude of the figures within the dataset, thus embedding values that are far from being Gaussian distributed, as it can be noticed from the scatterplots in Figs. 15 and 16, where some outliers[13] affect the model.

All in all, it is possible to sustain that the spread does not seem to be positively correlated with density. Rather, the coefficients for NYC and London indicate the opposite. For Sao Paulo and Rome, despite the high p-values obtained, the values are in the range of −0,28 and 0,13. Thus, even if the probability to encounter the null hypothesis is higher, it is unlikely to find a positive correlation.

Table 5 and Figs. 17–20 summarize the main statistics concerning the standardized coefficients obtained while correlating the SVI with COVID-19. It stands out how all coefficients present a positive value.

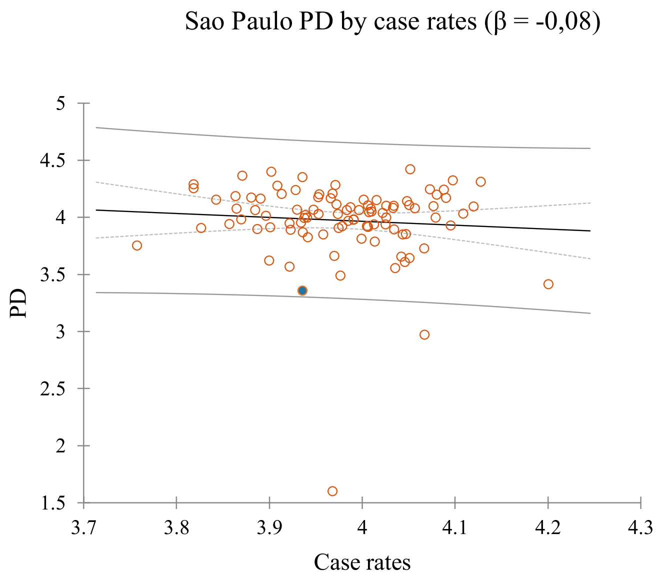

Fig. 16. Scatterplots and coefficients for the correlations between PD and case rates.

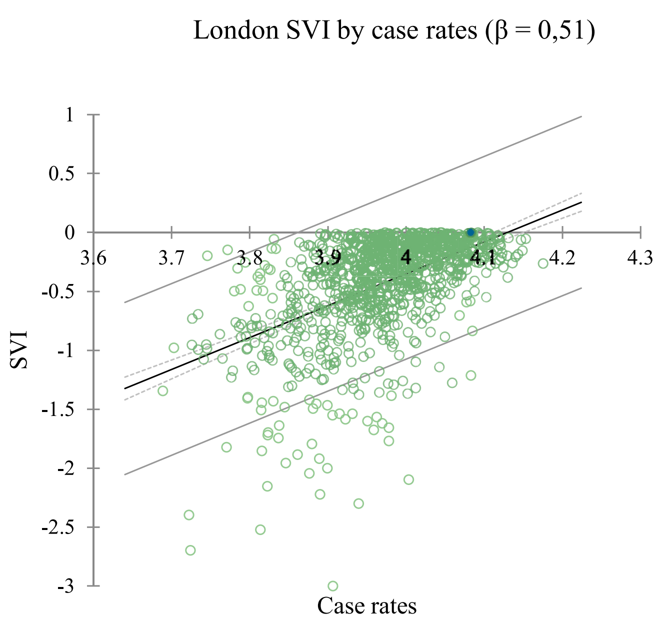

Fig. 17. Scatterplots and coefficients for the correlations between the SVI and case rates.

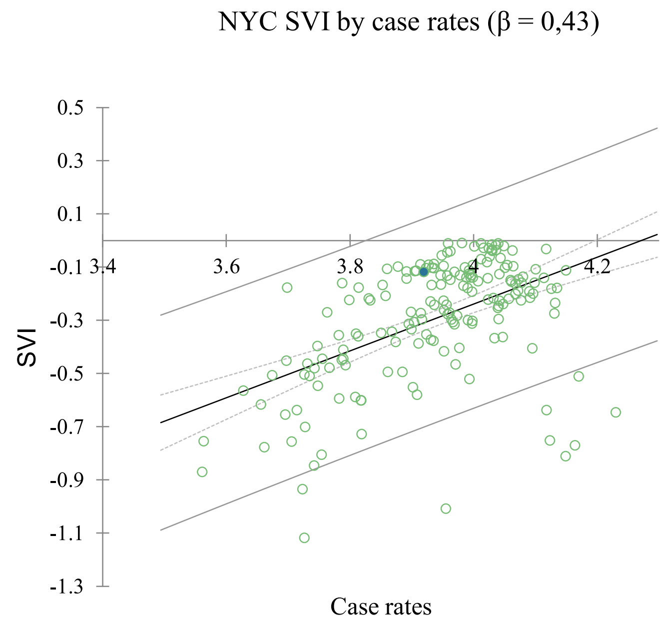

Fig. 18. Scatterplots and coefficients for the correlations between the SVI and case rates.

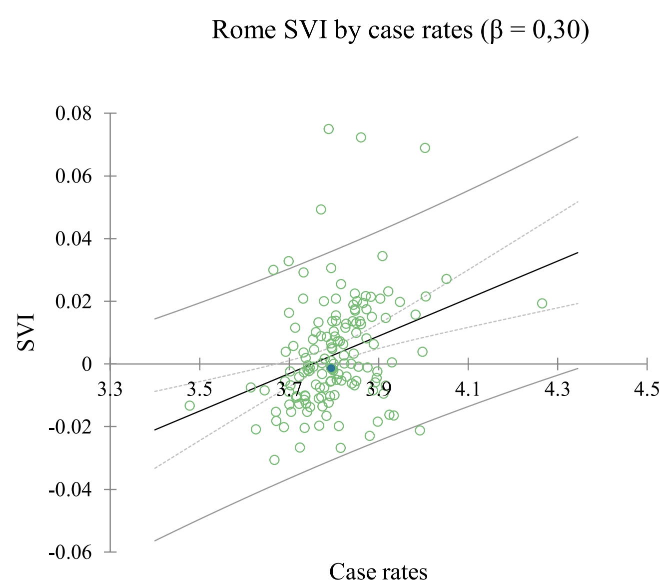

Fig. 19. Scatterplots and coefficients for the correlations between the SVI and case rates.

Moreover, the magnitudes span from moderate to significant (ranging from 0,25 to 0,51). London displays the highest coefficient (0,51), whereas Sao Paulo has the lowest (0,25). NYC and Rome stand in between (0,43 and 0,25, respectively). The p-values (Pr > |t|) are close to zero for all case studies, thus, there is a lower chance of encountering a null hypothesis. These results suggest that the coefficients found are significant, with lower standard deviations (ranging from 0,03 to 0,10) and low p-values (<0,05).

All in all, the results lead to believe that there is a positive linear correlation in place between the Social Vulnerability Index and the spread of the pandemic. The strength of such relationship varies across the case studies; it is stronger in NYC and London, and weaker in Rome and Sao Paulo, although always standing in the range of a moderate correlation. Given the complexity of the phenomenon, the values obtained through a singular index can be deemed to be relevant.[14]

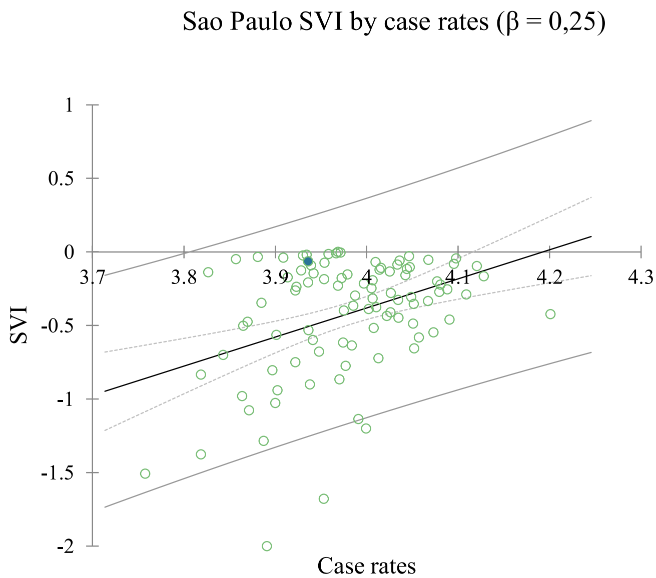

Fig. 20. Scatterplots and coefficients for the correlations between the SVI and case rates.

6. Discussion: which density and which vulnerability?

Overall, there are two main findings that need to be critically discussed. On the one hand, it was found that there is no significant positive correlation between population density and the spread of the virus. On the other hand, social vulnerability seems to be positively linked to the diffusion of the pandemic. The question, however, is: How can we interpret these results? Which critical lens do we need to apply? Are these two results "independent" or are they connected somehow? Here I argue that the answer lies in the way we conceptualise density and vulnerability.

Why do we see that density is not correlated with the spread of COVID-19? The traditional understanding of density as a measure of physical concentration is becoming increasingly influenced by relational factors, including connections between individuals, economic activities, physical-environmental characteristics, and ever-changing urban dynamics in both time and space. Consequently, when considering density, it is crucial to acknowledge not only its spatial aspect related to physical proximity, known as *topographical density* (measured by the ratio of inhabitants to land surface area and its various variations commonly used in geographical analyses), but also another form of density known as *topological density* (Small, MacDonald, & Sousa, 2020) focusing on the relationships that manifest between the mobile and immobile elements of space (McFarlane, 2016). These two types of density do not represent separate phenomena but rather distinct and complementary properties that reflect how human communities have historically organized themselves during the urbanization process driven by spatial agglomeration forces (Cremaschi, Salone, & Besana, 2021, pp. 5–31). The analysis carried out in this paper, at this specific intra-city spatial scale, evidences the discrepancy between *topographical* and *topological* density.

How does the difference in the conceptualisation of density affect our understanding of social vulnerability then? Which relational factors affected the most vulnerable and what patterns of relations exposed them during the pandemic? Besides the elements employed in this research, I argue for two possible lines of further inquiry.

For starters, we need to account for the different intensity and modalities of mobility that distinguishes vulnerable groups. The need to travel, whether for accessing essential services or attending their in-person jobs, could have exposed them to greater risks. Li et al. (2021) for instance found that low-income populations in Sao Paulo were more prone to experience fatal COVID-19 effects due to mobility and socioeconomic status. This brings us to the second aspect: the nature of employment available to vulnerable individuals and its impact during the pandemic. Maroko et al. (2020) for instance found that areas of high COVID-19 transmission in New York City were characterized by working-class neighbourhoods, where a significant number of service workers and those in "essential services" were employed. People in these occupations might have faced a higher risk of infection compared to white-collar workers, many of whom were able to work remotely during the pandemic. Clearly, the factors above are not meant to be mutually exclusive, nor are they meant to be exhaustive. Nevertheless, they can be taken as part of that network of relations that constitute topological density.

Besides the aforementioned potential integrative avenues for further investigation, there are aspects that limit the scope of this study. Firstly, although being all representative of intra-city dynamics, the case studies' spatial units of reference did not have the same area or scale of aggregation. Thus, it is not possible to ascertain whether the same results would have been obtained by having the data at equal scale. Secondly, the Pearson's correlation coefficient, like covariance itself, can only account for linear correlations between variables and ignores numerous other kinds of relationships. Thirdly, testing procedures, preventive measures, and operational protocols for disease containment can vary significantly from context to context. This variance has prompted some researchers to raise doubts about the reliability of the data when it comes to accurately gauging the extent of the contagion

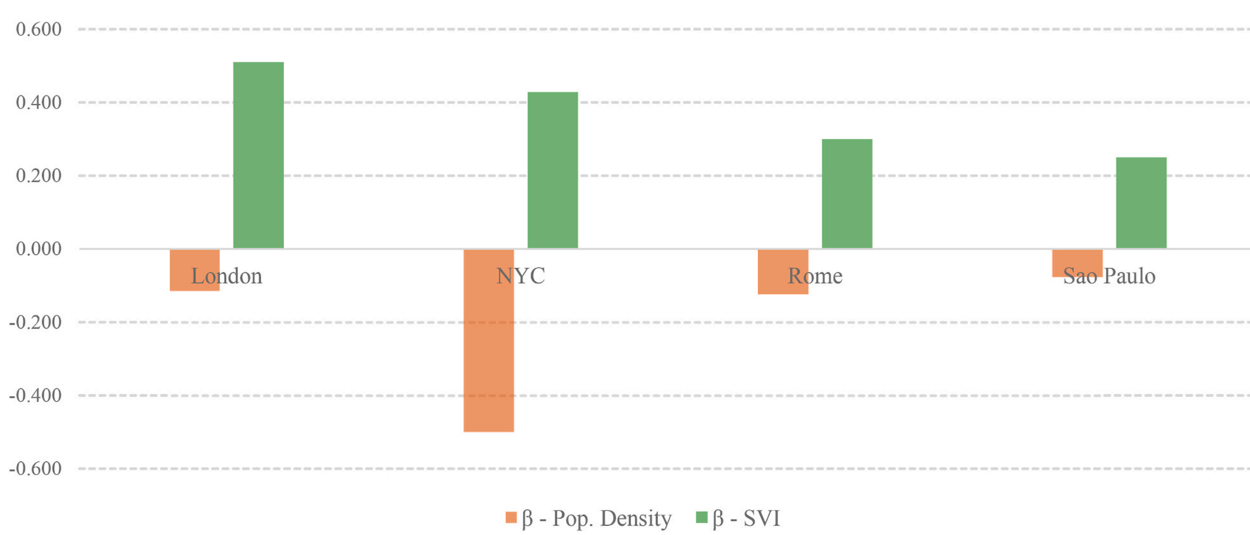

Fig. 21. Comparison of standardized coefficients.

and using it to derive precise quantitative indicators. The same concerns also pertain to the data employed in this study.

7. Conclusions: beyond and yet within density

The paper had a dual purpose: firstly, contributing to the ongoing discourse on the connection between population density and COVID-19 in urban areas, and secondly, investigating the spread of the pandemic in relation to socio-spatial vulnerabilities.

The analysis revealed two main findings. Firstly, there is no significant correlation between population density and COVID-19 spread. Secondly, social vulnerability is positively associated with the pandemic's diffusion. However, rather than taking the outcomes as a ready-to-go product, I invite a more reflexive and critical understanding of the results by questioning how density and vulnerability are conceptualised and intertwined. I believe traditional measures of density based on physical concentration should be supplemented by an understanding of relational factors and connections within communities. This includes topographical density as well as topological density, which examines relationships between mobile and immobile elements of space. The conceptualisation of density, I argue, also shapes our understanding of social vulnerability, particularly through the lens of topological density. Mobility patterns, employment characteristics, and household conditions contribute to the vulnerability of specific populations. These factors interact within the network of relations inherent to topological density and ultimately, I believe, shaped the exposure to the pandemic.

7.1. Notes

1. The Centers for Disease Control and Prevention (CDC) is the national public health agency of the United States. It falls under the Department of Health and Human Services. The primary objective of the organization is the preservation of public health and safety through the management and avoidance of illness, injury, and disability both domestically and abroad. The CDC concentrates national focus on creating and implementing disease control and prevention. It concentrates particularly on infectious diseases, foodborne pathogens, environmental health, workplace safety and health, health promotion, injury prevention, and educational initiatives aimed at enhancing the health of Americans.
2. For further details on the methodology employed for the construction of the indexes see Flanagan et al. (2011) or Centers for Disease Control and Prevention (2020).
3. The Organization Data Service publishes files created by the ONS on their behalf that link Postcodes to the Middle Layer Super Output Area. Output Areas (OA) were made up for census purposes, and to provide yearly census estimates at the lowest geographical scale
4. A similar index, referred to as "Climate Just data", is used by the city of London to identify which areas may be harmed the most by climate change. It seeks to "raise awareness about how social vulnerability, combined with exposure to hazards such as flooding and heat, can result in uneven impacts in different neighbourhoods, resulting in climate disadvantage" (Mayor of London, 2022). Therefore, whereas some variables and indicators used to construct the index do overlap with the SVI, others, for example the vicinity to the ground in case of flood, were more tailored for environmental hazards vulnerability.
5. The specific variables taken to construct the SVI were: 1) % Unemployed out of economically active population 2) Total Mean Annual Income per Household (£), 3) % Population with no High School Diploma, 4) % Population >65, 5) % Population <15, 6) % Population with a disability (day-to-day activities limited a lot), 7) % Lone parents with dependent children, 8) % Overcrowded Households (bedrooms), 9) % Households with no car. The proportion of overcrowded households in each MSOA was calculated using 2011 Census data, which classifies households in England by occupancy rating based on the number of bedrooms in the household, as also did by Daras et al. (2021).
6. These estimates are prior to the COVID-19 outbreak, and therefore, do not represent any changes to NYC's population because of COVID-related migration.
7. For NYC, the SVI is based on 15 different census estimated variables and determines the relative vulnerability of each census tract in the United States. Each variable is categorized into one of four themes: socioeconomic status (below poverty, unemployed, income, no high school diploma), household composition and disability (aged 65 or older, 17 or younger, older than age 5 with a disability, single parent households), minority status and language (minority, speaks English 'less than well'), housing and transportation (multi-unit structures, mobile homes, crowding, no vehicle, group quarters).
8. At the hearing held on 24 January 2017 by President Giorgio Alleva before the Parliamentary Commission of Inquiry into the security conditions and the state of decay of cities and their suburbs, ISTAT undertook to extend the analysis relating to the sub-municipal areas of the municipalities of Rome and Milan to the other 12 capital municipalities of the metropolitan cities and to expand the battery of indicators proposed at that time.
9. The selection of elementary indicators was guided by the need to identify indicators with a good degree of validity (e.g., capable of effectively representing the main dimensions of meaning), among the variables made available by the census survey. The specific indicators selected were: 1) % Population 25–64 years of age, illiterate, and literate without educational qualifications 2) % Households with 6 or more members 3) % Young (parent's age below 35 years) or adult (parent's age between 35 and 64 years) single-parent families on the total number of families 4) % Households with potential welfare hardship indicating the share of households composed only of elderly people (65 and over) with at least one member over 80 years old 9) % Population in crowded conditions as the percentage ratio between the population living in: i) dwellings with a surface area of less than 40 m2 and more than 4 occupants ii) in 40–59 m2 and more than 5 occupants iii) in 60–79 m2 and more than 6 occupants, and 59 m2 and more than 5 occupants, iv) 60–79 m2 and more than 6 occupants, and the total population living in occupied dwellings 10) incidence of young people outside the labour market and training 11) % Households in potential economic struggle. For further information about the methodology and the construction of the index, the author would suggest the reader to visit ISTAT (2011).
10. The data was retrieved from the TABNET, an online platform created by the Municipality of Sao Paulo, an application developed by DATASUS that allows tabulations by crossing several variables according to the user's interest. The databases are updated weekly. Since the subject involves COVID-19 (Severe Acute Respiratory Syndrome, Influenza Syndrome, and Deaths) cases are geocoded and made available with the analysis units requested by the applicant.
11. There were estimates also for the year 2020, however, after consultation with a member of SEADE, the data was found to account for the impact of COVID-19. Therefore, to avoid any sort of issues of endogeneity, the previous estimates were used.
12. The variables used for Sao Paulo were 1) Illiteracy rate of the population aged 25 and over 2) % Population aged 25 and over who have completed high school 3) % Of poor population 4) Average per capita income 5) Unemployment rate for the population aged 18 and over 6) % Population living in households with density greater than 2 people per bedroom 7) % Mothers who are heads of households, without complete primary education and with at least one child under 15 years of age, out of the

total number of mothers who are heads of households 8) % People in households vulnerable to poverty and dependent on the elderly 9) % population <17 10) % population >65

13. The scatterplots reveal the presence of some outliers. In principle, it was decided not to remove any observations from the datasets for two main reasons. Firstly, it is not possible to ascertain the cause of such outliers as it may be linked to mistyping or any other human-related factors. Secondly, the presence of outliers is part of the findings as they represent "anomalies" that could potentially be part of further investigation. They may help raise questions on the elements that made specific areas of the city differ from the overall trend of the city. Nevertheless, some further analyses and robustness checks have been carried out to ascertain that, even in the case these outliers are removed, the results are not altered significantly. The observations that were out of the interval of confidence (95%) were removed from the datasets and the correlations were run again. For what concerns the correlations between COVID-19 cases and SVI, in the case of London, 53 out of 983 observations (corresponding to the 5.4%) were removed. The new β value obtained was 0.50. In the case of NYC, 9 out of 177 observations (corresponding to the 5.1%) were removed. The new β value obtained was 0.61. In the case of Rome, 6 out of 144 observations (corresponding to the 4.2%) were removed. The new β value obtained was 0.33. In the case of Sao Paulo, 2 out of 96 observations (corresponding to the 2.1%) were removed. The new β value obtained was 0.25. For what concerns the correlations between COVID-19 cases and Population Density, in the case of London, 40 out of 983 observations (corresponding to the 4.1%) were removed. The new β value obtained was −0.13. In the case of NYC, 5 out of 177 observations (corresponding to the 2.8%) were removed. The new β value obtained was −0.51. In the case of Rome, 9 out of 155 observations (corresponding to the 5.8%) were removed. The new β value obtained was −0.14. In the case of Sao Paulo, 2 out of 96 observations (corresponding to the 2.1%) were removed. The new β value obtained was −0.06. Hence, following the robustness checks detailed just above, it is safe to say that the outliers do not affect the results significantly.
14. For sake of completeness, also the correlation between the SVI and PD was tested. The resulting coefficients suggest that in London (0,17) NYC (0,15), Rome (−0,25) and Sao Paulo (−0,10) there is no strong positive or negative correlation.

Data availability statement

The data that support the findings of this study are available at the URLs provided in Appendix 1. These data were derived from resources available in the public domain. For Rome, the data concerning the spread of the pandemic is not publicly available, and it was provided upon official request to the *Dipartimento di Epidemiologia del Servizio Sanitario Regionale del Lazio (DEP)*.

Disclosure statement

No potential conflict of interest was reported by the author.

Author statement

I wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

I confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

I confirm that I have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing I confirm that I have followed the regulations of my institution concerning intellectual property.

I confirm that Emanuele Sciuva is the sole author of this article.

I understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). I confirm that I have provided a current, correct email address which is accessible by the Corresponding Author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. Data sources

City	Theme	Variable	Source	URL
London	***Covid-19***	N° of cases	PHE	URL
	Statistical boundaries	MSOAs Boundaries	London Datastore	URL
	Demography	MSOAs population estimates	ONS	URL
	Social vulnerability	SVI	ONS	URL
NYC	***Covid-19***	Case rates	NYC DOHMH	URL
	Statistical boundaries	MODZCTAs boundaries	NYC Open Data	URL
	Demography	MODZCTAs population estimates	U.S. Census Bureau	URL
	Social vulnerability	SVI	CDC	URL
Rome	***Covid-19***	Case rates	DEP Lazio	Not available
	Statistical boundaries	ZUBs boundaries	Roma Capitale Open Data	URL
	Demography	ZUBs population estimates	ISTAT	URL
	Social vulnerability	SVI	ISTAT	URL
Sao Paulo	***Covid-19***	N° of cases	TABNET	URL
	Statistical boundaries	MSOAs Boundaries	Dados abertos	URL
	Demography	MSOAs population estimates	Fundação SEADE	URL
	Social vulnerability	SVI	Dados abertos	URL

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