spazio aperto

Covid-19's spatiotemporal patterns within cities: a global comparative study

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The first confirmed cases of Covid-19 were discovered around the end of 2019 in Wuhan, Hubei Province, China, and the world as we knew it changed from then on. Whereas most of the research has focused on the meso-urban scale, there is only a limited number of studies focusing on the distribution of cases at a spatially granular scale within cities, throughout time. This work aims at filling this gap, by drawing different cities across the globe into a comparative project, where the spread of the pandemic is analysed throughout three distinct 'waves' of the pandemic. This study sheds light on the current debate about the variability of results across time and space, and how insights need to be reframed by accounting for the spatiotemporal dynamicity of Covid-19.
Keywords: Covid-19; comparative urbanism; spatial analytics

Pattern spazio-temporali del Covid-19 nelle città: uno studio comparativo globale
I primi casi di Covid-19 sono stati scoperti alla fine del 2019 a Wuhan (Cina) e da quel momento il mondo come lo conoscevamo è cambiato. Mentre la maggior parte della ricerca si è concentrata sulla scala meso-urbana, solo un numero limitato di studi si concentra sulla distribuzione dei casi a scala spaziale granulare all'interno delle città, nel corso del tempo. Questo lavoro mira a colmare questo gap, coinvolgendo diverse città del mondo in un progetto comparativo in cui la diffusione dei contagi viene analizzata nel corso di tre distinte 'ondate' della pandemia. Lo studio fa luce sull'attuale dibattito riguardo la variabilità dei risultati nel tempo e nello spazio, e su come i risultati debbano essere riformulati tenendo conto della dinamicità spazio-temporale della pandemia.
Parole chiave: Covid-19; urbanistica comparativa; analisi territoriale

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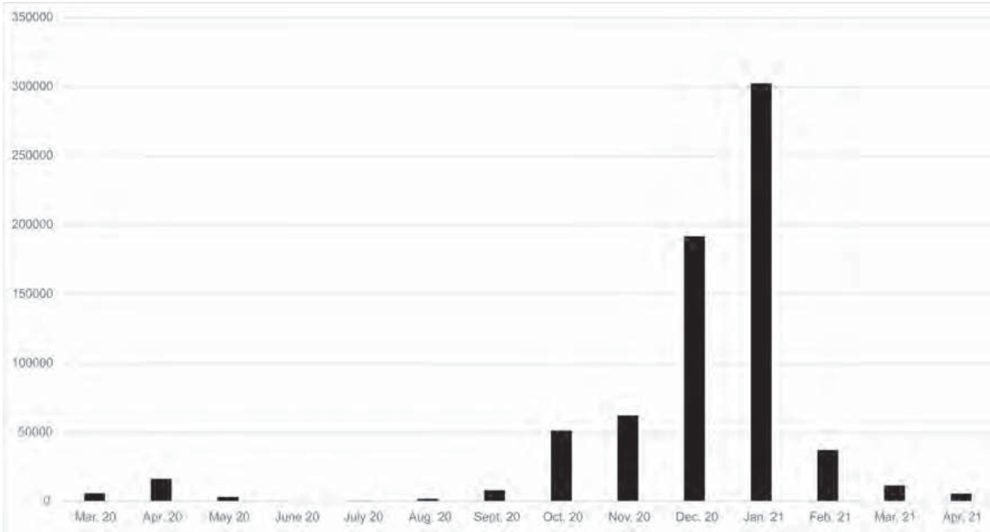
An epidemic explosion is a typical, however dramatic, case of spatial spread, a well-known and studied topic in geography. The concept of diffusion in geography involves the movement of a certain event, or set of events, in space and time, and determines, as a result, a process and a pattern (Hagerstrand, 1967; Gould, 1969; Morrill, 1970). Covid-19, from this perspective, has pushed researchers from all over the world to learn more about the pandemic's driving mechanisms and spatiotemporal dissemination patterns (Hu *et. al.*, 2021; Kim, Bostwick, 2020; Li S.L. *et al.*, 2021; Li B. *et al.*, 2021). However, despite a large number of studies, there is still only limited research that has looked at the distribution of cases on a spatially granular scale, examining the distribution and evolution of spatial patterns across time *and* within cities' subunits. As Casti (2020) notes, the spatial features of the Covid-19 outbreak, such as the outbreak locations and the intensity and distribution of its spread in affected territories, reveal the rapid speed at which the contagion has propagated, emphasizing the need for a territorial analysis that takes on a space-time dimension. In my opinion, conducting studies of this kind can aid in identifying spatial weaknesses, which can serve as a starting point to reconsider territorial policies in the aftermath of the Covid-19 pandemic (Casti, 2020). The use of mapping, from this standpoint, promotes reflexivity by encouraging critical examination of the events that shape our understanding of the differential spread of the virus across affected territories. With this in mind, I have chosen to undertake a longitudinal study that utilizes gis-based spatial modelling techniques to analyse and disaggregate the spatial spread of the pandemic across various cities. The work is divided into six sections. Following this introduction, the second part reviews the milestones in the field of the geography of health, showing the most relevant insights as well as the limits that we should try to overcome in contemporary literature. The third section discusses the research technique and procedures used in this study. The fourth part goes over the data that was used to conduct the analysis and the investigation's findings are presented in the fifth part. Finally, the sixth section covers the major insights and highlights the work's primary aspects.

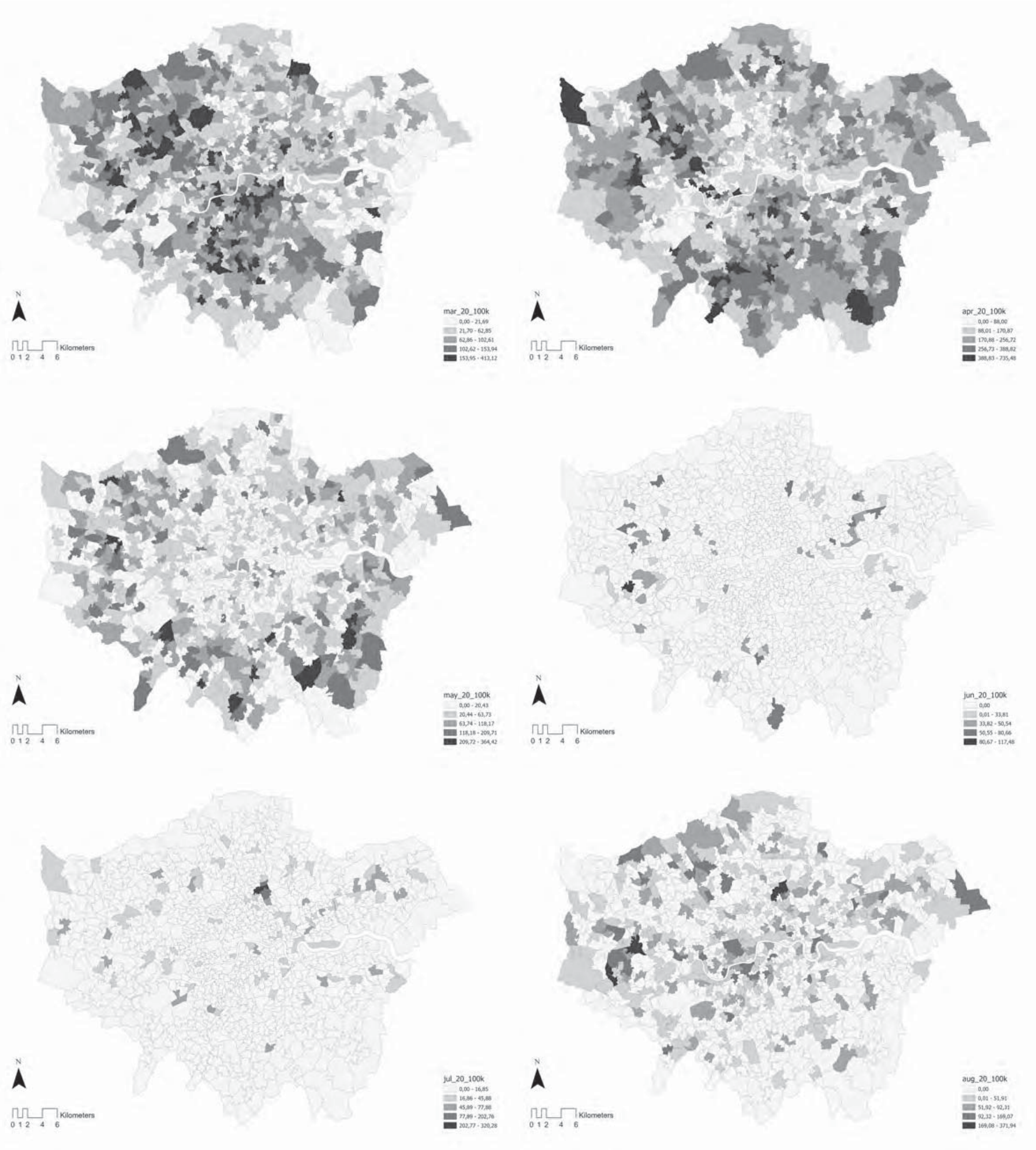
Background: Geography of health and Covid-19

In medical geography, there are two common approaches to spatial diffusion. The first approach involves specifying a diffusion model based on a general birth and death process and then inferring or simulating spatial patterns of mortality or morbidity. The second approach involves studying a sequence of map patterns and



1. Bar chart Covid-19 cases in London. Data source: Public Health of England (PHE). Chart: author elaboration.

attempting to determine the range of disease diffusion processes that could be responsible for generating them (Hagget, 1976).
Since Hagerstrand's classic Swedish work, many geographers have focused on studying the diffusion of a 'single wave'. However, some researchers have taken on the more challenging task of examining the diffusion of multiple waves. Specifically, Cliff and Haggett (Haggett, 2001; Haggett, Cliff, 2003; Cliff, Haggett, Smallman-Raynor, 2004; Cliff, Haggett, 2006) described how diffusion processes take place in the form of 'spatial diffusion waves', which start from one or more locations and then spread outwards in various ways, covering larger areas. These geographers have modelled the spread of epidemics, including the relationship between epidemic events in space and time and their wave-like nature. Epidemic spread is a combination of expansion and relocation, starting in a particular region and expanding as it moves to new areas. The spread can occur through 'contagion' when the virus spreads through direct contact, 'networked' when it follows the networks of relationships and flows between individuals and places, 'hierarchical' when it is more intense from top to bottom, and 'cascade' when it is generally more intense from higher to lower hierarchically important centers. The 'wave' can also change direction, once the population recovers, and the regions where the infection first developed return to normal. In geography, the diffusion wave generally follows a theoretical 5-step path: Onset, Youth, Maturity, Decay, and Extinction.
As foundational as the work of Cliff and Hagget is, it is not 'immune' to limits. Specifically, they conducted their research in self-enclosed systems (e.g., islands) as it was simpler to "isolate" epidemics from other confounding elements such as urbanization and mobility, as they themselves admitted. Given these limitations, along with the relevance of the impact of Covid-19 in dense urban settlements, it is now more critical than ever to examine the phenomenon in less self-contained systems by leveraging the technological resources available today.
Contemporary research has responded to the challenge. Numerous researchers have focused on deciphering the intricate spatiotemporal patterns of Covid-19, examining various spatial levels (e.g., Hu *et al.*, 2021; Kim, Bostwick, 2020; Li S.L. *et al.*, 2021; Li B. *et al.*, 2021), and striving to uncover ways to prevent and control the pandemic by detecting high-risk areas and determining the factors that may facilitate its transmission in urban settings (Li S.L. *et al.*, 2021; Li B. *et al.*, 2021; Mansour *et al.*, 2021). For instance, Zhonghua, Xing, and Xue (2020) investigated the spatiotemporal characteristics of the pandemic's spread in Guangdong province, concluding that the prevention and control measures in place were effective, and high-risk locations were largely concentrated in the province's economically developed districts.
Furthermore, many researchers have investigated the influence of socioeconomic factors. Maroko, Nash and Pavilonis (2020) compared patient hotspots in New York City (NYC) and Chicago and found that hotspots in NYC comprise neighbourhoods of the working and middle classes. Other multivariable investigations have been carried out. Almagro and Orane-Hutchinson (2022), for example, developed a regression model based on a set of environmental variables to assess the statistical significance of the relationship between neighbourhood measures (such as population density, commuting patterns, and health insurance controls) and response variables (such as demographic status and Covid-19 incidence) in NYC neighbourhoods. They discovered that the profession played a significant role in the Covid-19 patterns they observed. This suggests that the understanding of the pandemic's spread entails a multitude of factors and elements at play.
The literature discussed above has helped us better comprehend the pandemic's distribution patterns and dynamics. However, there are still gaps that need to be addressed. On the one hand, existing research has primarily focused on city, regional or national scales, with a few studies conducted at a lower spatial scale. While city and regional-level analyses can reveal important information about



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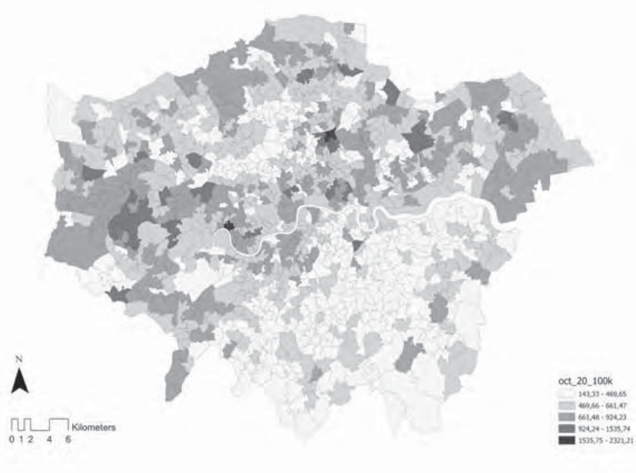
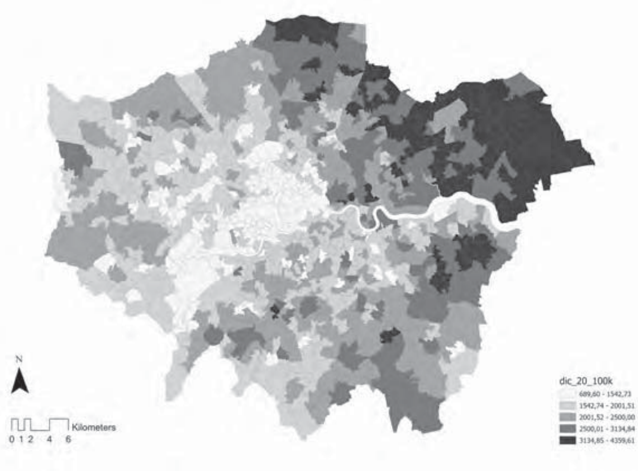
6	7

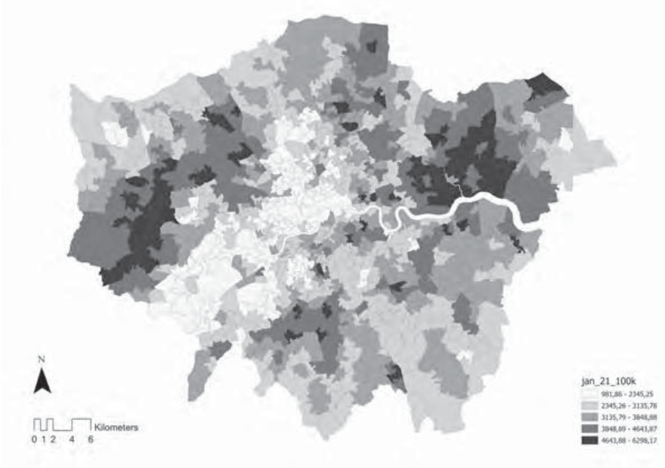
2-18.London Covid-19 case rates by MSOA. Data source: Public Health of England (PHE).
Maps: author elaboration.


N
Kilometers
0 1 2 4 6
sep_20_100k
0,00
0,01 - 72,35
72,36 - 127,53
127,54 - 210,95
210,96 - 582,09


N
Kilometers
0 1 2 4 6
oct_20_100k
143,33 - 469,65
469,66 - 661,47
661,48 - 924,23
924,24 - 1535,74
1535,75 - 2321,21


N
Kilometers
0 1 2 4 6
nov_20_100k
146,31 - 496,93
496,94 - 697,24
697,25 - 928,49
928,50 - 1268,10
1268,11 - 2100,67

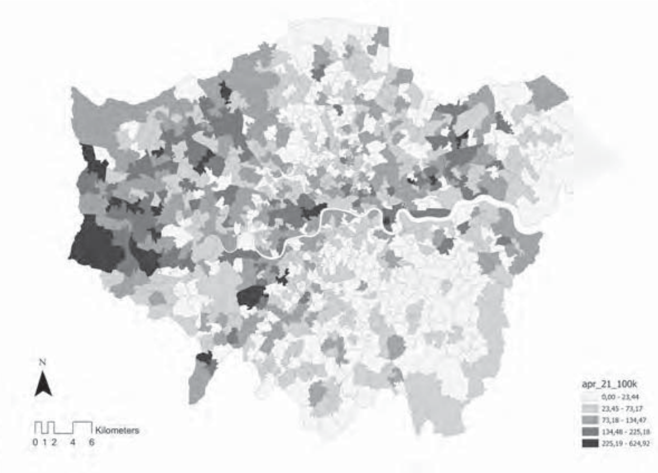

N
Kilometers
0 1 2 4 6
dic_20_100k
689,60 - 1542,73
1542,74 - 2001,51
2001,52 - 2500,00
2500,01 - 3134,84
3134,85 - 4359,61

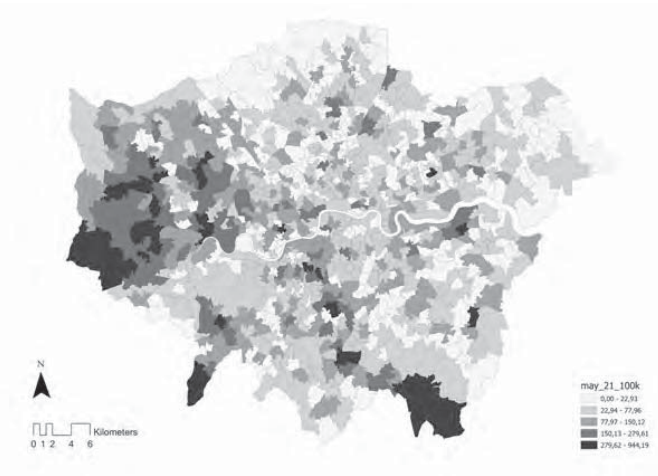

N
Kilometers
0 1 2 4 6
jan_21_100k
981,86 - 2345,25
2345,26 - 3135,78
3135,79 - 3848,88
3848,89 - 4643,87
4643,88 - 6298,17

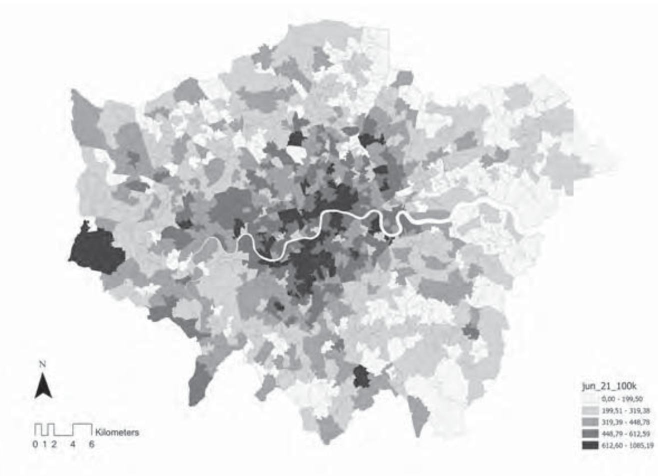

N
Kilometers
0 1 2 4 6
feb_21_100k
51,64 - 252,39
252,40 - 388,21
388,22 - 541,29
541,30 - 766,46
766,47 - 1264,10

8	9
10	11
12	13


N
0 1 2 4 6 Kilometers
mar_21_100k
0,00 - 54,57
54,58 - 120,38
120,39 - 197,97
197,98 - 311,66
311,67 - 538,74


N
0 1 2 4 6 Kilometers
apr_21_100k
0,00 - 23,44
23,45 - 73,17
73,18 - 134,47
134,48 - 225,18
225,19 - 624,92


N
0 1 2 4 6 Kilometers
may_21_100k
0,00 - 22,93
22,94 - 77,96
77,97 - 150,12
150,13 - 279,61
279,62 - 944,19


N
0 1 2 4 6 Kilometers
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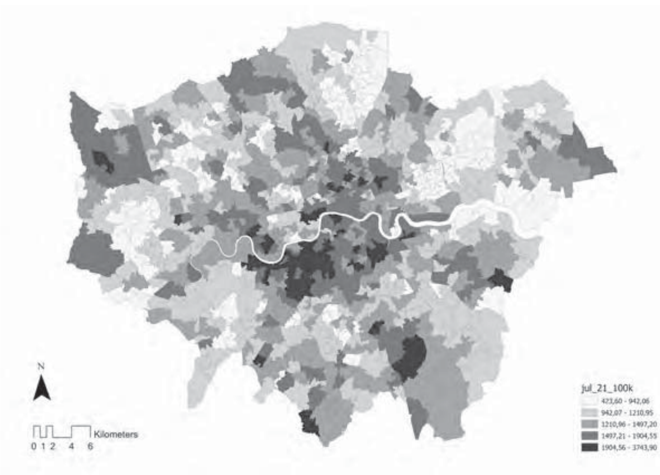
0,00 - 199,50
199,51 - 319,38
319,39 - 448,78
448,79 - 612,59
612,60 - 1085,19


N
0 1 2 4 6 Kilometers
jul_21_100k
423,60 - 942,06
942,07 - 1210,95
1210,96 - 1497,20
1497,21 - 1904,55
1904,56 - 3743,90

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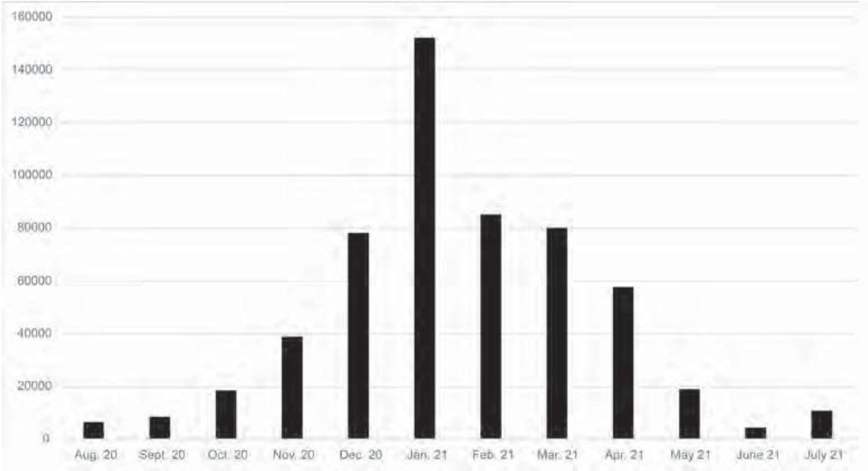


19. Bar chart Covid-19 cases in New York City. Data source: New York City Department of Health & Mental Hygiene (DOHMH). Chart: author elaboration.

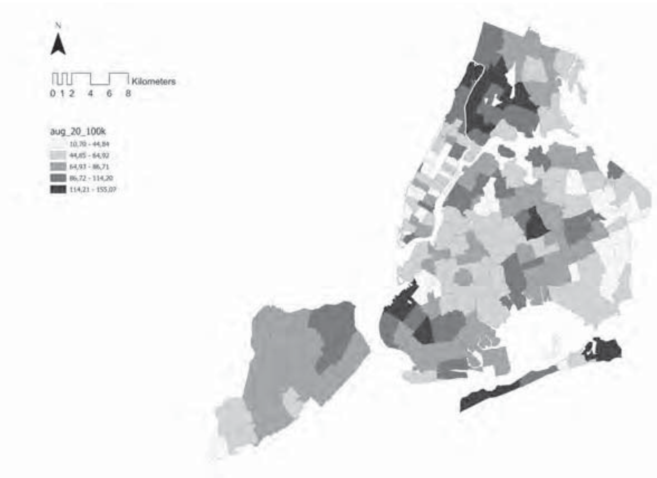
the disease's overall transmission patterns and dynamics, as well as the efficiency of response strategies and policies, they fall short of providing precise intra-city dynamics and variations. Conducting a granular scale-based investigation could help address this gap. On the other hand, a limited number of studies have focused on studying the distribution and evolution of spatial patterns within cities' subunits over time. It is possible that employing overall figures to study the pandemic's spread, might lead to different results compared to the analysis of the phenomenon when accounting for only a portion of it.

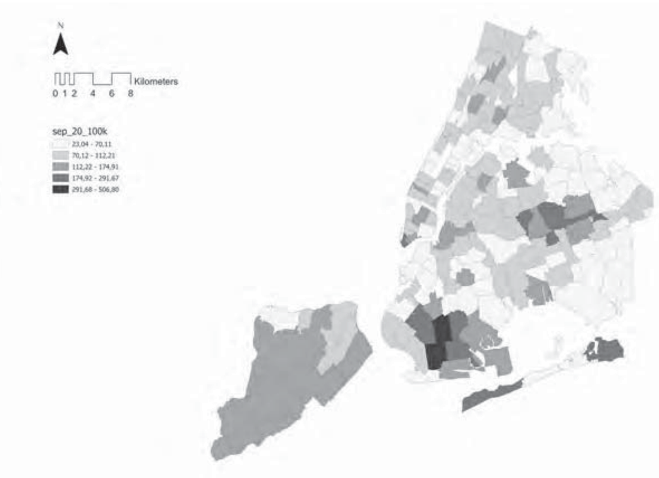
Methodology and methods: GIS to track spatiotemporal patterns across cities

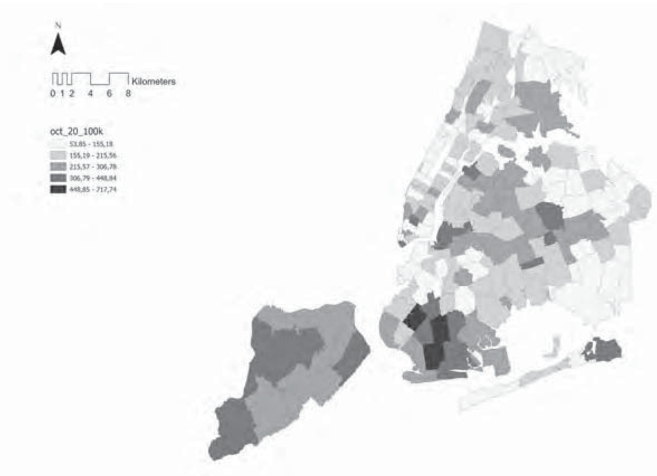
The case study approach was chosen as the methodology for this project. It is an approach that, according to Yin (2018), enables the analysis of contemporary phenomena in their context, particularly when their borders are hazy. The next paragraphs will provide an explanation of the logic behind the case study selection and comparison criteria. Notably, the MUAP (Modifiable Area Unit Problem) (Wong, 2004) presented significant challenges in the development of a purely quantitative approach where all instances were mechanically drawn together, as a potential statistical bias in the interpretation of the results could have been introduced. This was due to the fact that the spatial unit of reference for the case studies was not equal in terms of area and scale of aggregation. As a result, the chosen case studies are numerically examined on an individual basis, and then the findings and insights are qualitatively compared across the different cities.
The data about the pandemic's spread is analysed using GIS and spatial statistics collected from institutional channels, organised by month of incidence and location of occurrence. This allows us to map the distribution of cases across space, and time. This exercise is, therefore, a descriptive examination of Covid-19, an attempt to scrutinise the pandemic's spatio-temporal spread in different contexts. It's an opportunity to delve deeper into the outbreak's patterns and allow divergences and convergences to emerge.
On a last note, graduated black and white maps, effective to visualise how the pandemic spread sequentially, were used to highlight the differences in impact across the units of the case studies. The maps were plotted through the GIS software using a 'natural break' system, where the software creates class breaks in a way that best groups similar values together and maximizes the differences between classes (ESRI, 2021).

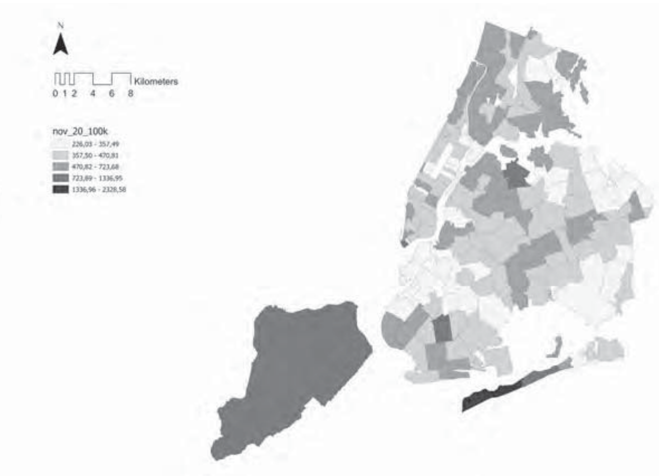
Case studies selection and rationale

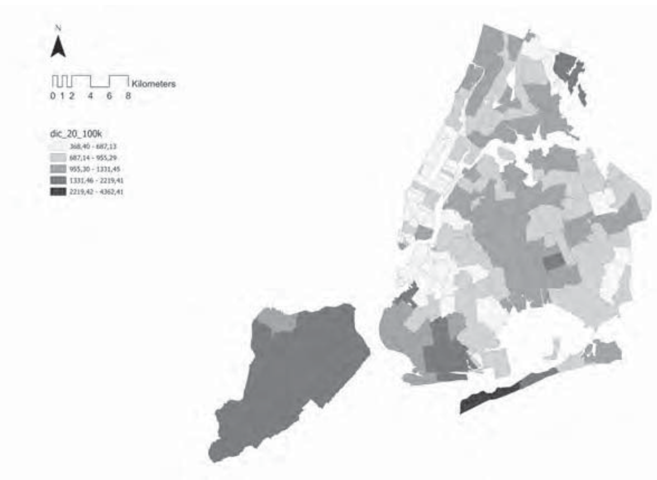
Only a few studies have examined the distribution of cases at a spatially granular scale inside cities, as well as the evolution of spatial patterns over time. Previous research, indeed, has primarily focused on the meso-urban scale. In this scenario, can comparative studies enhance our understanding of Covid-19's socio-spatial dynamics? What sort of comparative methodology ought to be envisioned?
According to Jennifer Robinson (2011: 1) «cities exist in a world of cities and thus routinely invite a comparative gesture in urban theorizing». Yet, comparative urbanism's framework has been skewed by grouping cities into categories like developed and developing, capitalist and socialist, thus limiting the possibility of cross-category research. The interest in making comparisons between radically different cities has, however, grown as 'globalization' has become more significant in the characterization of urban phenomena during the past ten years. Consequently, there is both a resurgence and a restructuring of comparative studies in the field of urban studies (Robinson, 2002; Robinson, 2006; Robinson, 2011; Robinson, 2016; McFarlane, 2010; Ward, 2008). To develop theoretical insights, academics are increasingly making comparisons between various urban contexts (e.g., McCann, Ward, 2011; Roy, Ong, 2011). Relatedly, implementing novel strategies

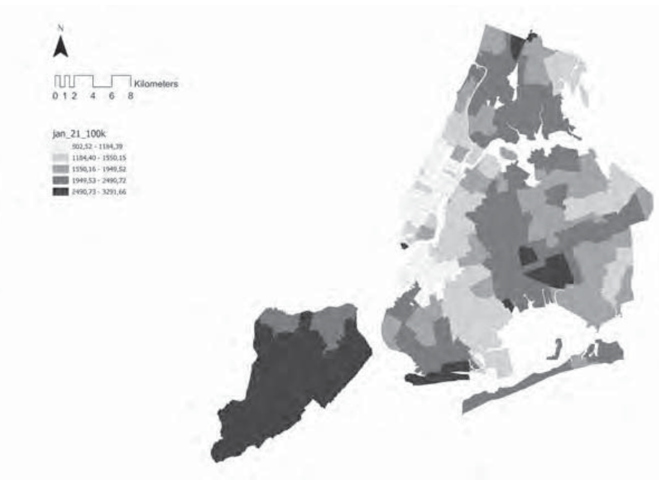












20	21
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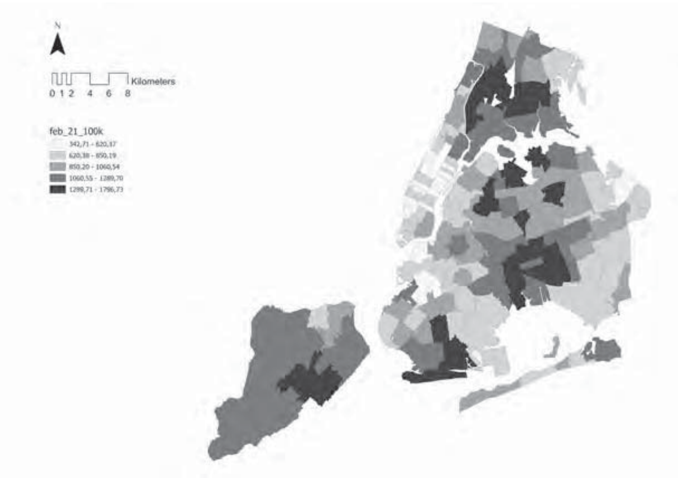
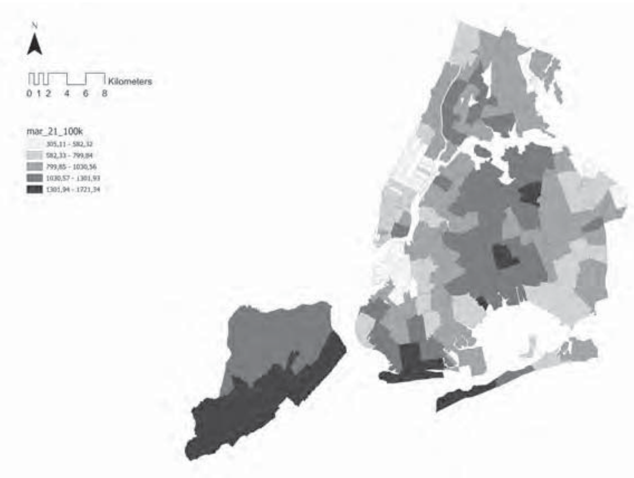
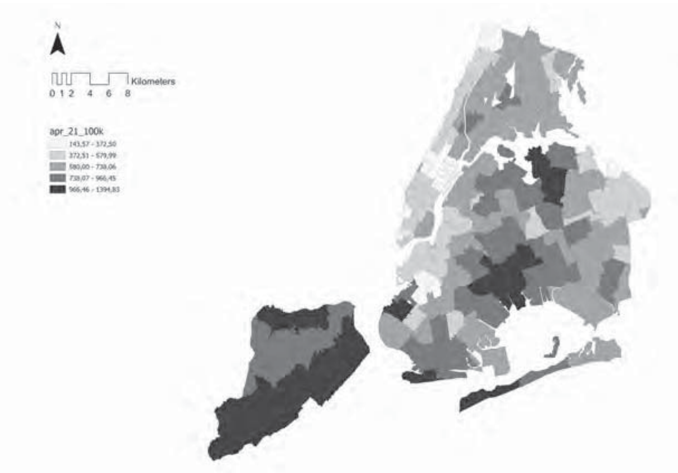
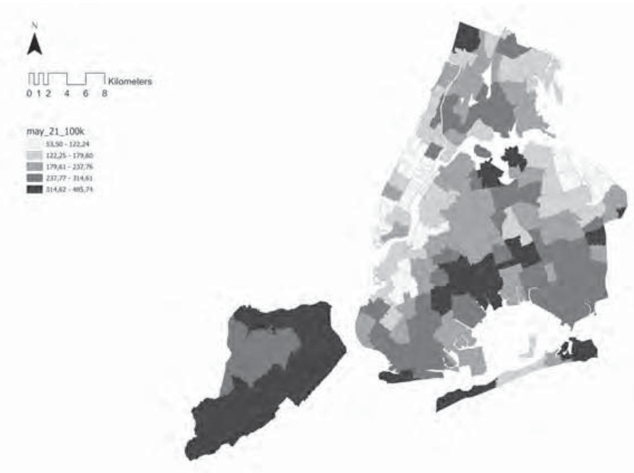
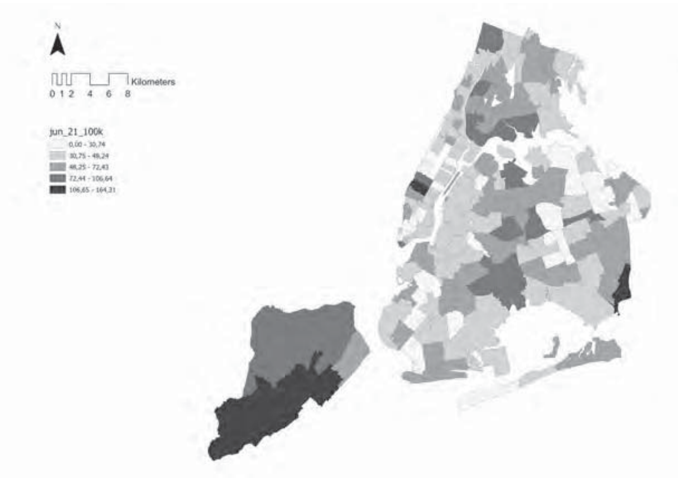
20 - 31. New York City Covid-19 case rates by MODZCTA. Data source: New York City Department of Health & Mental Hygiene (DOHMH). Maps: author elaborations.

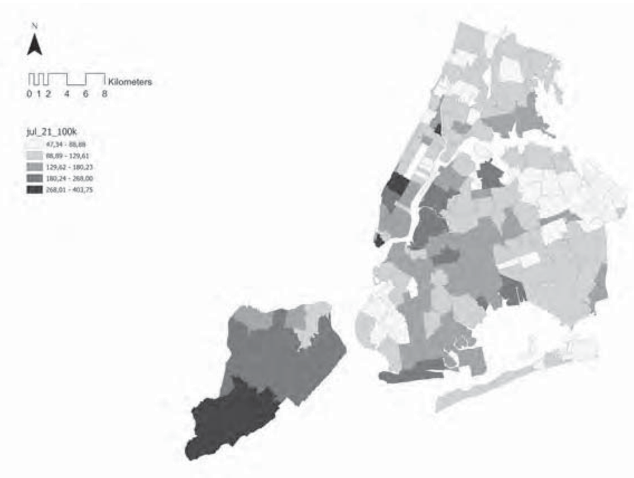












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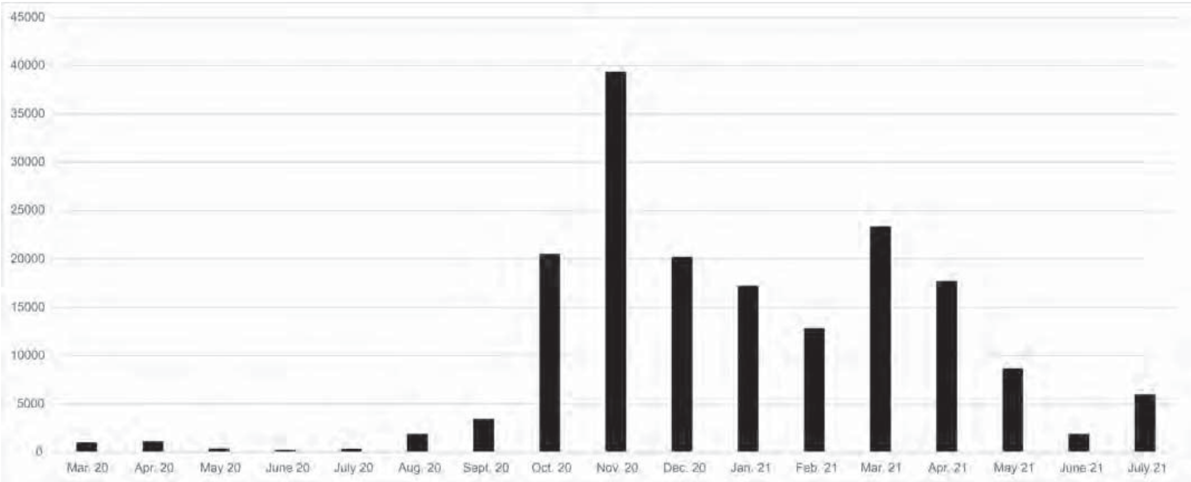


32. Bar chart Covid-19 cases in Rome. Data source: Dipartimento di Epidemiologia del Servizio Sanitario Regionale del Lazio (DEP). Chart: author elaboration.

and techniques is essential to assessing the diversity of urban experiences in the modern world as the challenge for researchers is to think and theorise about diverse cities. However, there has been limited comparative research spanning across, for instance, the 'Global North' and the 'Global South' divide (Robinson, 2011). Building on these observations, Jennifer Robinson claims for a global comparative urbanism by incorporating radically different cities (McFarlane, Robinson, 2012), where 'diversity' is questioned and made operative. The purpose is to restrict and call into question the applicability of ideas that originate in one location and are then universally applied. The richness and diversity of the phenomenon occurring in different cities may be overlooked if a finding is 'overstretched' to anywhere (or anytime). By employing a comparative approach across diverse instances, we can take advantage of divergences and convergence to explore the nature of specific phenomena, such as the spatiotemporal variation of the spread across the cities, and how this may or may not have an impact on the validity of results when certain contextual and temporal features are ignored. In congruence with this position, the case studies selected – London, New York City, Rome, and Sao Paulo – were all significantly impacted by the pandemic and yet they had different approaches to its containment. Moreover, since the 'waves' are the main spatio-temporal units of analysis, the four cities presented almost coinciding periods of epidemic and endemic character, favouring a comparative exercise. Finally, from a practical point of view, they all had a suitable database storing data on the spread of Covid-19 at the sub-city level, thus allowing the analysis of intra-city patterns.

Data: Covid-19 cases disaggregated in time and space

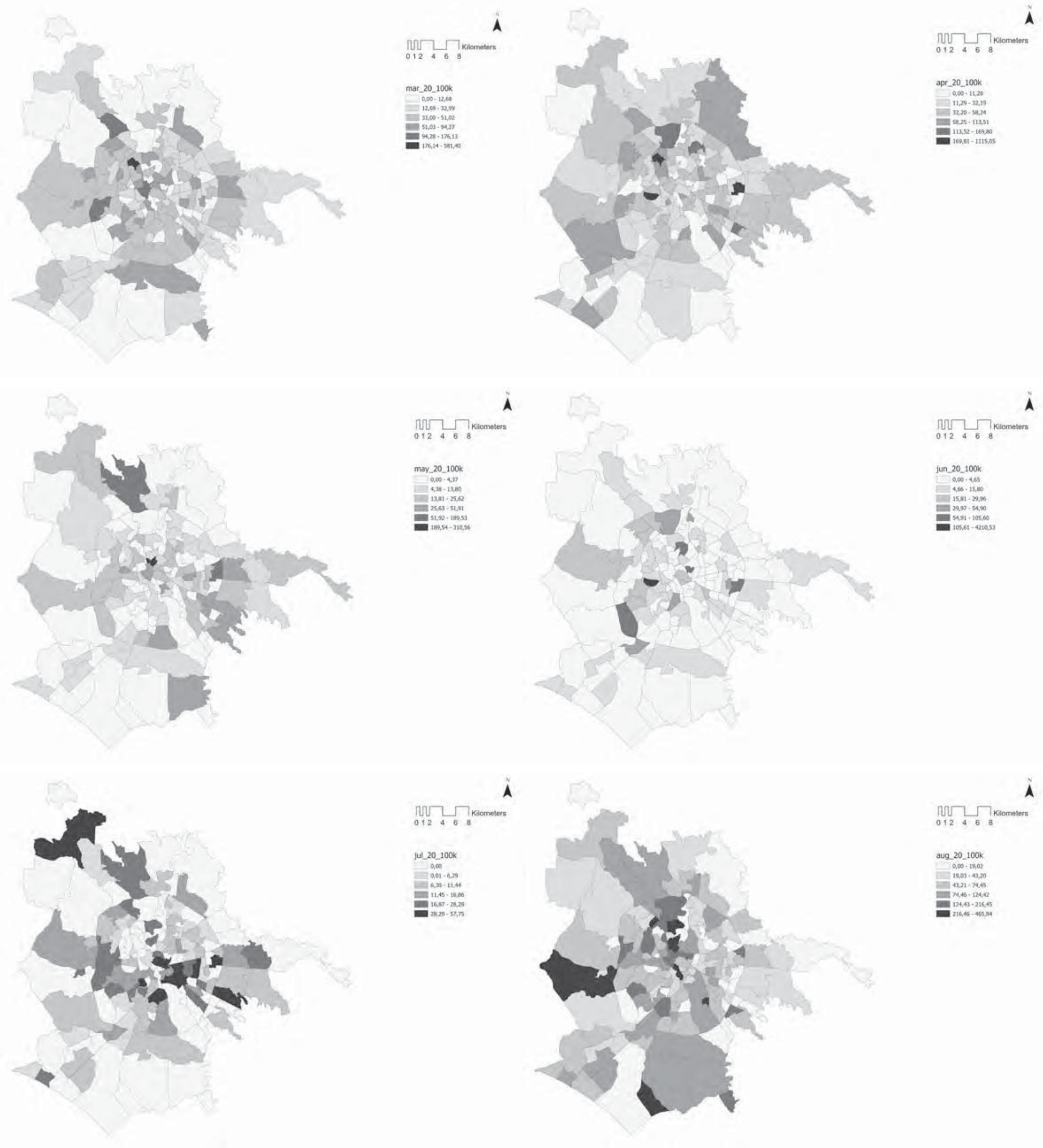
Since individual health variables, such as age and the presence of comorbidities, can have a greater impact on death and hospitalization rates (de Andrade *et al.*, 2020; Giorgi Rossi, *et al.*, 2020; Jassat *et al.*, 2021) the author chose to focus on Covid-19 case rates for this study. Case rates, or the number of cases per 100,000 citizens, have been used to map and analyse the pandemic in all case studies, favouring the comparison of different units across cities.[1]

The data for London was obtained from the PHE (Public Health England) website and organised by Middle Layer Super Output Areas (MSOAs). The data for the pandemic spans the period from March 29th, 2020, to July 25th, 2021. The data was collected as total incidence per MSOA and normalized per 100k inhabitants (dividing by the ONS population estimates for 2019 and multiplying by 100.000).

The data for New York City was taken from the GitHub open folder of the NYC DOHMH (New York City Department of Health and Mental Hygiene) and organized according to MODZCTAS (Modified Zip Code Tabulation Areas). The time span is from the 8th of August 2020 until the 24th of July 2021. The data was provided in the form of rate, derived using interpolated intercensal population estimates updated in 2020.

The DEP *Lazio* (Department of Epidemiology of the Regional Health Service - *Lazio*) submitted Covid-19 data for Rome upon request, thus, it was not readily available. The data was already disaggregated at the *Zona Urbanistica* (ZUB) scale. 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, which was computed using istat's (Italian National Institute of Statistics) population forecasts from 2020.

The information about the epidemic in Sao Paulo was obtained from TABNET, a web-based platform built by the city of Sao Paulo. Covid-19 data was divided into three categories: E-SUS-VE Flu Syndrome (GS), severe acute respiratory syndrome (SRAG), and deaths. The first was used to account for the pandemic's spread, already broken down into Administrative Districts (*Distritos Administrativos*). The time span is from the 1st of March 2020 until the 27th of July 2021. The data was obtained in the form of



33	34
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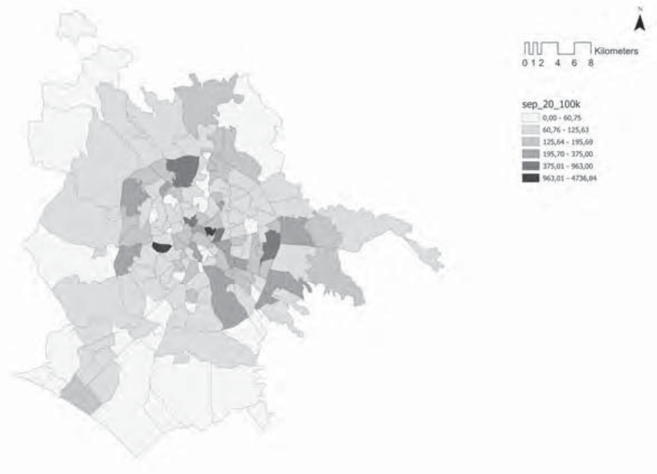
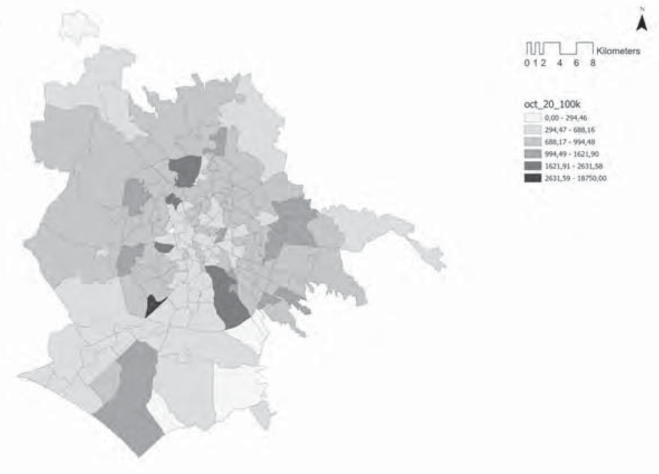
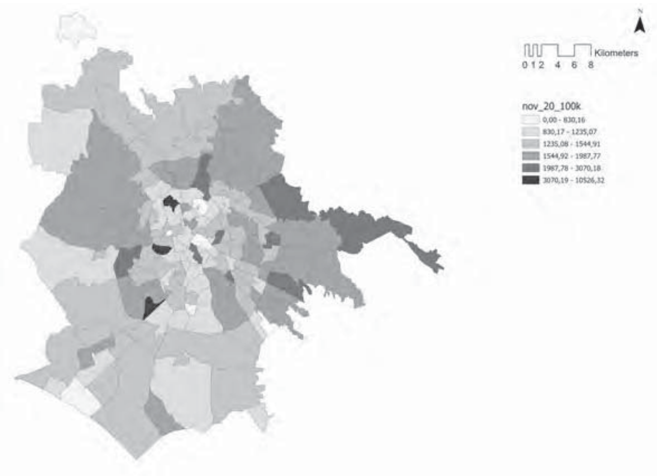
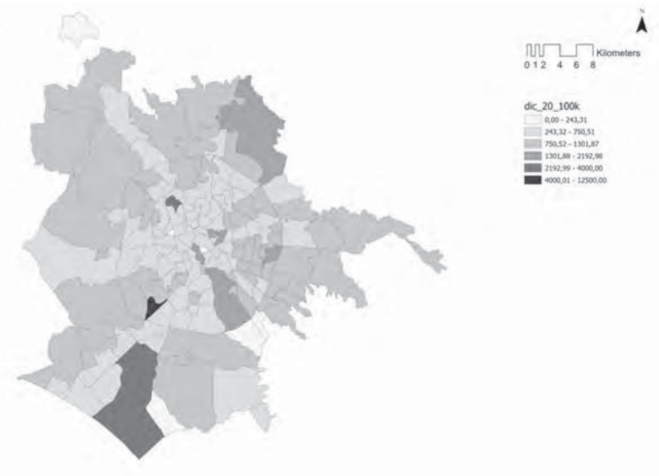
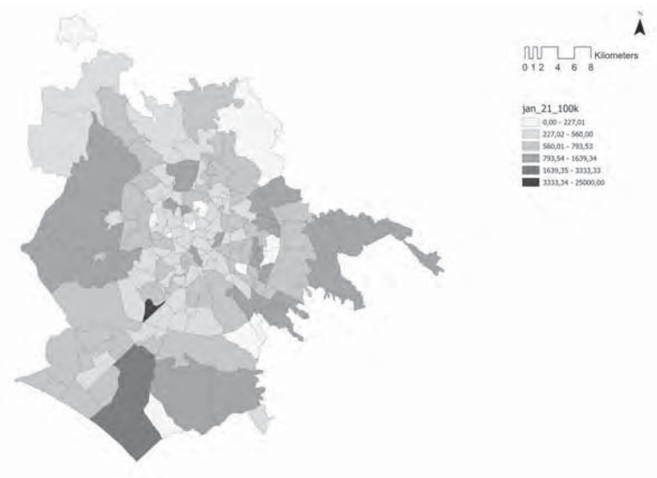
33-49. Rome Covid-19 case rates by ZUB. Data source: Dipartimento di Epidemiologia del Servizio Sanitario Regionale del Lazio (DEP). Maps: author elaborations.

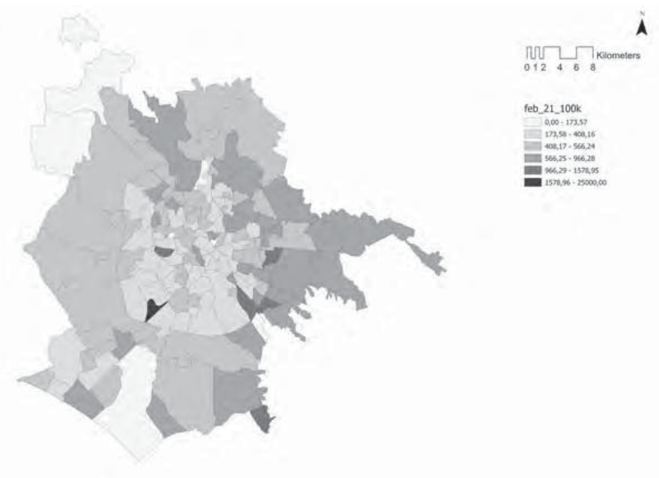












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41	42
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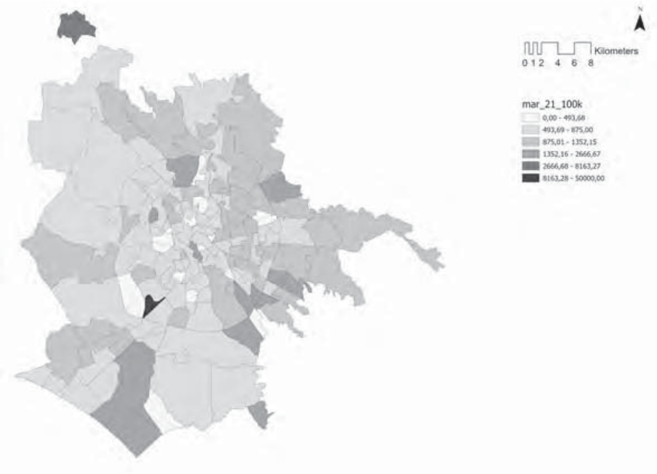
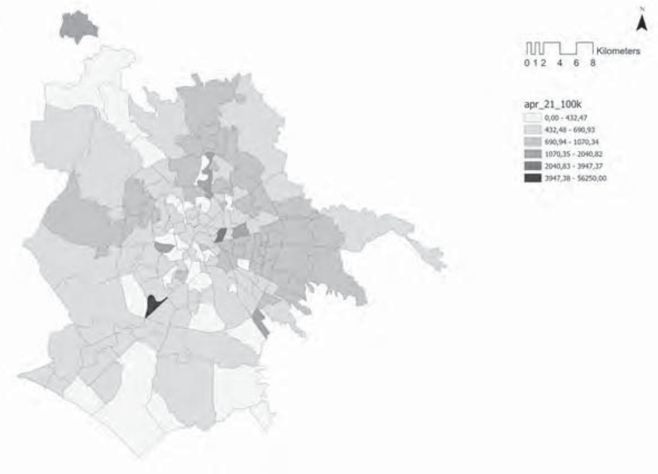
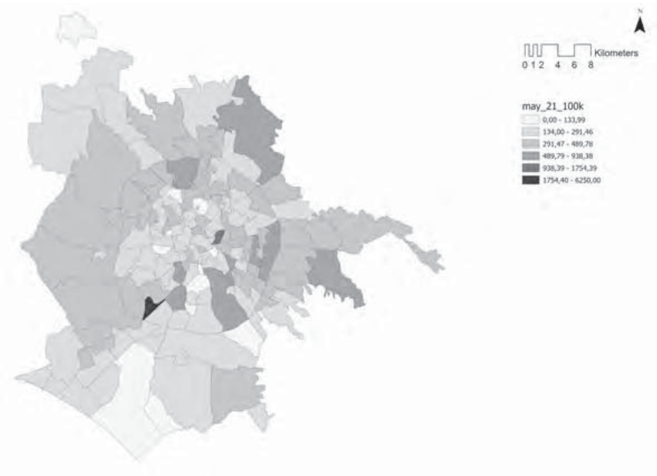
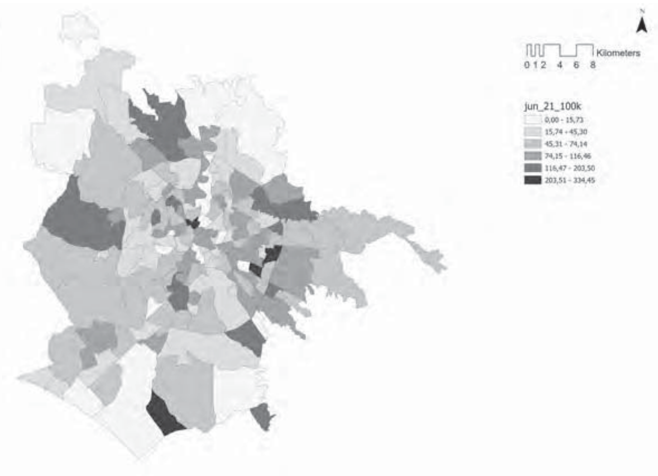
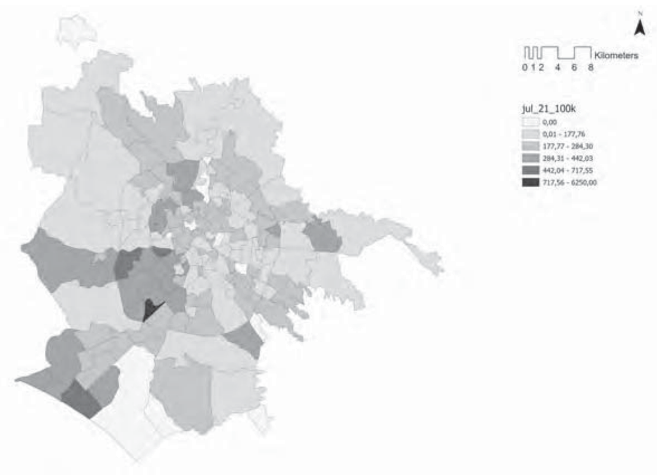

N
0 1 2 4 6 8 Kilometers
mar_21_100k
0,00 - 493,68
493,69 - 875,00
875,01 - 1352,15
1352,16 - 2666,67
2666,68 - 8163,27
8163,28 - 50000,00


N
0 1 2 4 6 8 Kilometers
apr_21_100k
0,00 - 432,47
432,48 - 690,93
690,94 - 1070,34
1070,35 - 2040,82
2040,83 - 3947,37
3947,38 - 56250,00


N
0 1 2 4 6 8 Kilometers
may_21_100k
0,00 - 133,99
134,00 - 291,46
291,47 - 489,78
489,79 - 938,38
938,39 - 1754,39
1754,40 - 6250,00


N
0 1 2 4 6 8 Kilometers
jun_21_100k
0,00 - 15,73
15,74 - 45,30
45,31 - 74,14
74,15 - 116,46
116,47 - 203,50
203,51 - 334,45


N
0 1 2 4 6 8 Kilometers
jul_21_100k
0,00
0,01 - 177,76
177,77 - 284,30
284,31 - 442,03
442,04 - 717,55
717,56 - 6250,00

45	46
47	48
49	

absolute incidence, and the rate was calculated using population estimates from *Fundação* seade (*The Fundaço Sistema Estadual de Analise de Dados*), which were updated in 2015.

Results: Covid-19 as a spatially dynamic phenomenon

London

In London, as the graph of incidence over time shows (fig. 1), we can roughly define three distinct waves. The first one, although minimal, was from March to April 2020. The second started in September 2020, picked in January 2021, and decreased in February 2021. The last wave, up to the date of retrieval of the data, began in June 2021 and was still growing in July 2021.

Starting from March 2020 (fig. 2), the central area hosted a greater number of cases compared to the outer units. The North-West, namely Brent, Barnet, and Ealing, accounted for a significant number of cases. From April 2020 (fig. 3), whereas the spread in some of the central areas of London started to decrease, like in the areas of Kensington and Chelsea or Westminster, others, like Hammersmith and Fulham, for instance, showed an increase in cases. Also, East and West London's cases grew. In general, it is possible to observe how the spread was pushed outwards, while simultaneously, the central areas showed decreasing figures, although not homogeneously. This trend is even more evident in May (fig. 4), where, despite the general drop in cases registered (from 16.464 to 3.403), the external areas accounted for most cases, proportionally speaking.

June, July, and August (figs. 5 to 7) present lower overall figures (225,412 and 2.016 respectively), even if rising over time, particularly in August when the figure quintupled. During June and July, most areas presented little if no cases. However, some hotspots could still be observed (e.g., Hackney), which draw attention to specific granular units within the entire city. In August, some patterns can be observed. Firstly, the number of cases grew in central London. Secondly, East, West and North London, previously presenting low case rates, start to show increasing figures. South London, on the other hand, presents lower case rates. The rising trend of August 2020 continued also in September (from 2.016 to 8.148) as shown in fig. 8. Here again the central part of London experienced an increase in case rate. The spread is highly scattered, but, contrarily to the beginning of the first wave, West and East London were affected the most. South and North London, which were proportionally more impacted in the first wave, are less affected in the second wave.

By observing the map of August, September, and October (figs. 7 to 9), it is possible to assert how the distribution of cases is roughly the same, although gradually exacerbated, with significant growth in East and West London. It appears the spread is roughly reversed, compared to the first wave (from South-North to West-East spread), although both suggest the beginning of the spread from the centre. The three-month period from November to January (figs. 10 to 12) was the most impactful, as shown by the overall cases (62.228, 191.911 and 302.508 respectively). The rate grew for almost all MSOAs except for a few exceptions (e.g., Merton). In this case, conversely to what was observed during the summer period, it might be potentially revealing to explore the reasons why specific units have shown a decreasing trend while the entire city experienced significant growth. Besides this, there are other patterns to observe during the second wave. Firstly, Central London had a lower rate than the rest of the city proportionally. Secondly, it is possible to notice how the spread initially affected East London more than other areas. It also spread to South, West, and finally North London, in an almost clockwise direction. From February to March 2021 (figs. 13 and 14), there was a decreasing trend in the overall cases, stabilising in April and May (figs. 15 and 16). Also in this case, West, East, and part of South London showed proportionally more significant figures, and, geographically speaking, the cluster of infections remained stable over time, although gradually declining. In the last wave (figs. 17 to 18), although just partial, there is a pick of cases in basically all the central areas, while the outward proportionally accounts for lower rates.

New York City

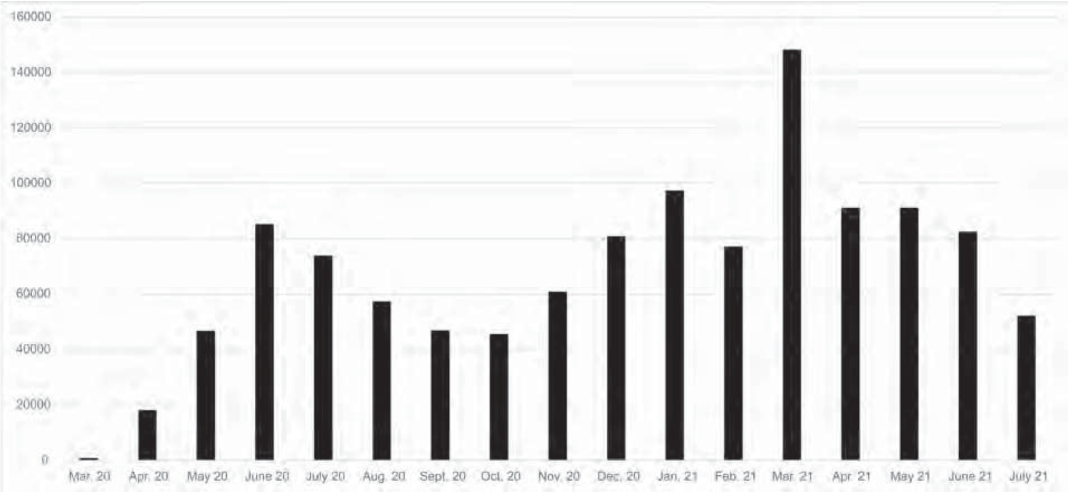
The data available for NYC starts from August 2020 (fig. 20), which coincides, approximately, with the beginning of the second wave. There are several spatial observations that can be put forward. Firstly, Manhattan is internally quite diversified, particularly in Lower and Upper West and East Side. Moreover, in August, certain areas are more affected than others. This is the case for the Bronx, Staten Island (apart from Tottenville), the southern part of Brooklyn, and the western and southern part of Queens like Breezy Point or Hamilton Beach.

In September, October and November (figs. 21 to 23) the overall rate of cases increased. The entire island of Manhattan shows a quasi-homogeneous distribution of rates, a trend that was already in motion in the previous months, although Upper Manhattan was still more affected. The eastern part of Queens (e.g., Douglaston) and the northeastern part of Brooklyn (e.g., Brooklyn Heights) had lower figures, besides a few exceptions such as Hillcrest and Kew Gardens, whereas the western part has comparatively higher rates. Staten Island, South Brooklyn and South Queens were still proportionally more affected.

In December and January (figs. 24 to 25), we can still observe an overall increase in cases, although with a different distribution. Whereas Manhattan (except for Upper Manhattan) has proportionally lower rates, besides the area of Stuy Town and the Business District, some other parts of the city, previously identified as the most affected, can now be more neatly recognised. Namely, the Bronx, Staten Island, the entire Queens, and South Brooklyn. There is therefore a trend in place: at the beginning of the wave the cases are more evenly spread, whereas it tends to segregate as the pandemic progress. A constant feature is that some areas, regardless of the specific timeframe of observation, are always proportionally more affected than the rest of the city.

On the other hand, as we observe February, March, April and May 2021 (figs. 25 to 29), periods within which the cases were declining, we see that the rates tend to be more even in Manhattan. In other words, whereas initially the Bronx and Upper Manhattan, for instance, displayed much higher rates compared to the rest of the island, from February to April (included), the proportions are seemingly rebalanced. In June (fig. 30), which also represents the valley, as shown from the graph (fig. 19), there is seemingly homogeneity across the entire city, except for Staten Island.

In July (fig. 31), which is the beginning of the third wave, we observe an overall growth. Interestingly, Lower Manhattan was amongst the most affected areas, while notoriously more vulnerable areas, like the Bronx or Queens, showed lower figures. Therefore, contrary to what happened at the beginning of the second



50. Bar chart Covid-19 cases in Sao Paulo. Data source: TABNET. Chart: author elaboration.

wave, the 'centre' of the city seems to account for proportionally more cases than other areas (besides Staten Island). Once again, as observed in London, there seem to be different distribution patterns as the analysis shifts from wave to wave.

Rome

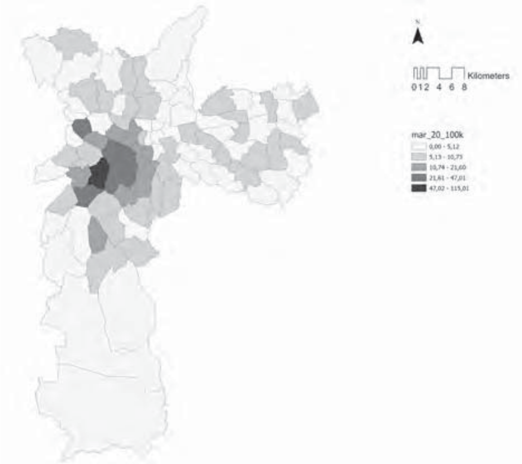
In Rome, starting from March 2020 (fig. 33), we observe a higher concentration of cases within the gra (*Grande Raccordo Anulare*), despite many scattered zubs with relatively low figures. The eastern and western parts were also significantly impacted. The southern and northern areas, instead, were comparatively less hit. In April (fig. 34), the spread also affected the previously marginally hit areas, except for the southern units, which remained proportionally less impacted. We can still see a great deal of heterogeneity within the gra, with zubs accounting for the highest rates (e.g., *Foro Italico* or *Villa Pamphili*). In May (fig. 35), the overall cases decreased (from 1.130 to 375), and the distribution of cases also varied compared to previous months. We observe a reduction in rates in many areas within the gra, although the pattern is maintained rather heterogeneous. Similarly, most of the external zubs showed a decreasing trend, except for the eastern part, where areas like *Torre Angela* or *Tor Vergata* maintained a seemingly stable trend. Notably, possibly in divergence with the previous case studies, here we observe several zones characterised by dramatically fluctuating figures within the space of a few months and in contrast with the trend of the surrounding areas (e.g., *Villa Pamphili*).

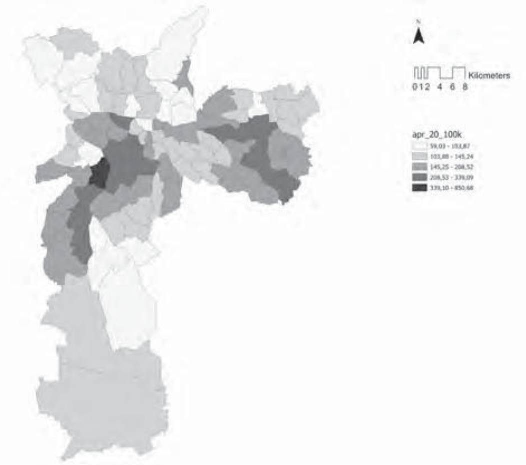
After a steady growth in June (fig. 36), the rates decreased again in July (fig. 37). In the former, we observe how *Villa Pamphili* accounts for almost the totality of the cases. It is of interest to explore the reasons behind this singularity. In July, despite the overall decline, the rates were seemingly more distributed within the gra, which also accounted for proportionally more cases than external areas. Nevertheless, some zones outside the gra also accounted for significant rates in July, especially in the eastern and northern sides. In general, it was possible to observe more evenness in the distribution of cases across the municipality in the first wave.

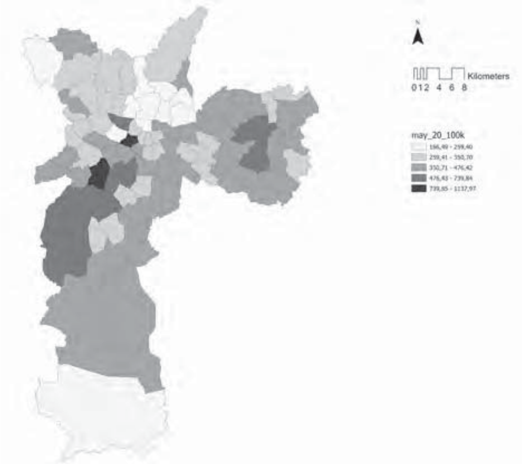
August's trend (fig. 38) is consistent with the one analysed in July, with a prevalence of cases within the gra. In the months that followed, specifically from September 2020 to May 2021 (figs. 39 to 47), despite the dramatic growth of cases across the entire city, as shown by fig. 32, there was a very consistent pattern in the distribution of cases. In fact, it is possible to assert that the whole municipality and its sub-areas were affected almost evenly throughout the period. Moreover, *Tor di Valle* accounted for the highest figures, constantly, over most of the timeframe of interest. This homogeneity in distribution, maintained for a relatively long period, differs from the observations gathered from the previous case studies of London and nyc. In fact, whereas for the two, the evenness in spatial distribution was maintained temporarily, or over short periods, in Rome, the pattern is maintained quite consistently for some months. In June (fig. 48), which represents the valley for the second wave, the spread is more heterogeneous, with a prevalence of rates within the gra, although there were still external areas significantly affected. Finally, in July, we observe a more homogeneous distribution of the rates (fig. 49).

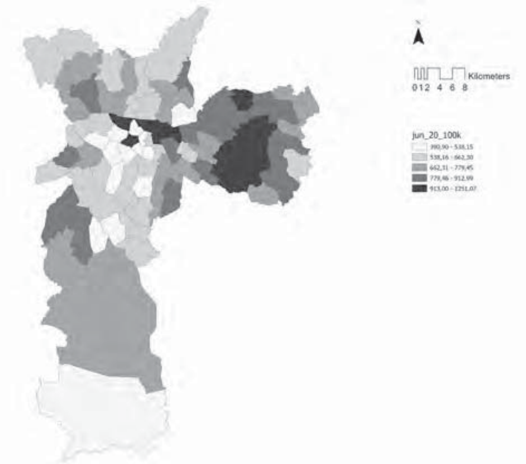
Sao Paulo

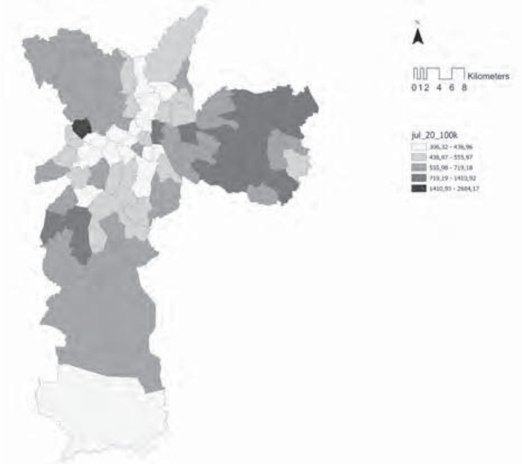
In Sao Paulo, from March to June (figs. 51 to 54), a period characterised by the overall growth of cases, the spread seems to start from the centre and spread outwards, as it happened for nyc and London. In contrast, in June, the proportional impact across the city was higher in the outer regions, with some exceptions, such as *Marsilac*, located deep south in the municipality of Sao Paulo. In this first phase, the areas mainly affected were found in the southwest (*jd Angela*, *Sao Luis* and *Capao Redondo*) and

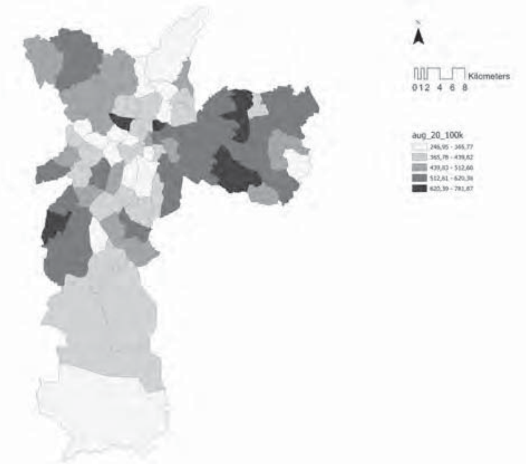






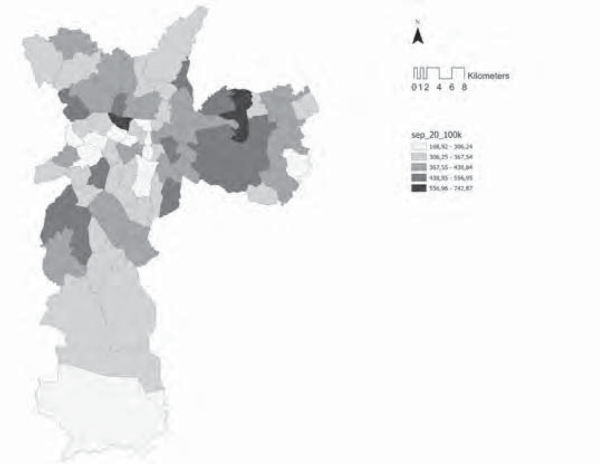


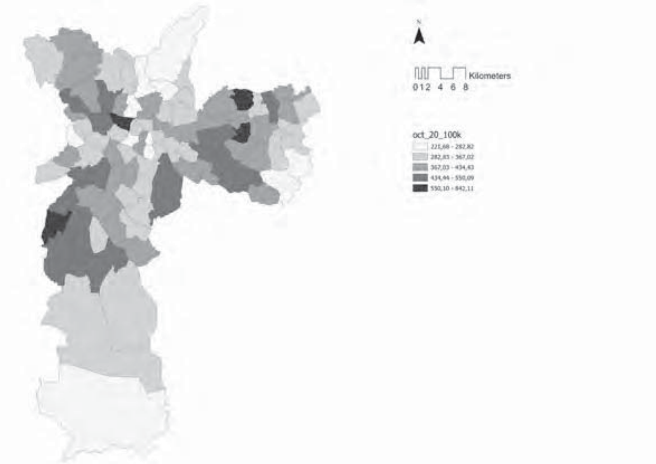


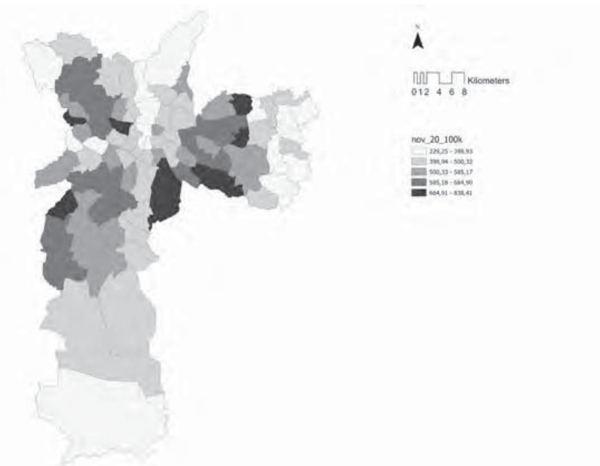


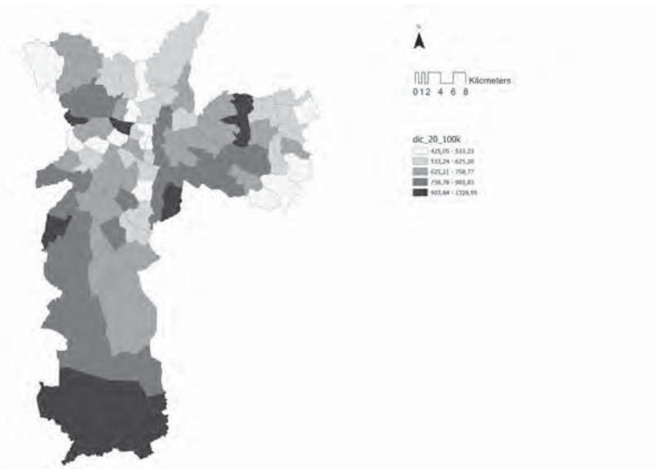
51	52
53	54
55	56

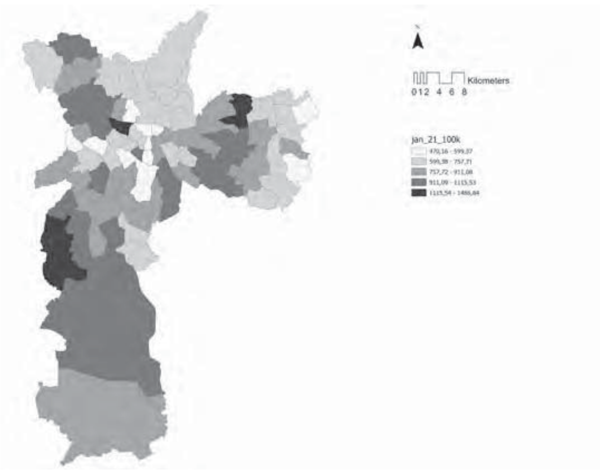
51-67. Sao Paulo Covid-19 case rates by Distritos Administrativos. Data source: TABNET.
Maps: author elaborations.

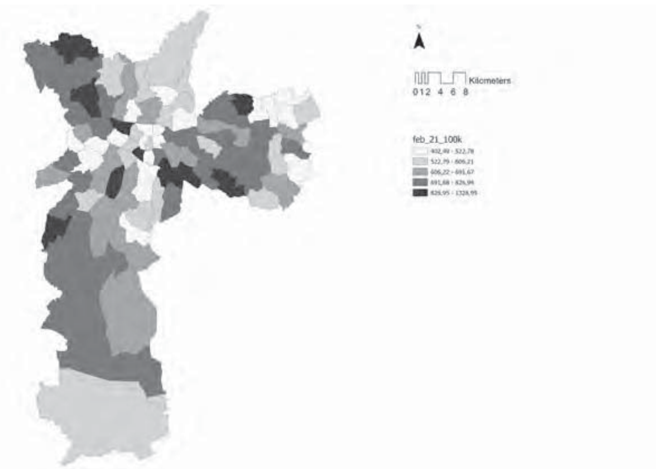




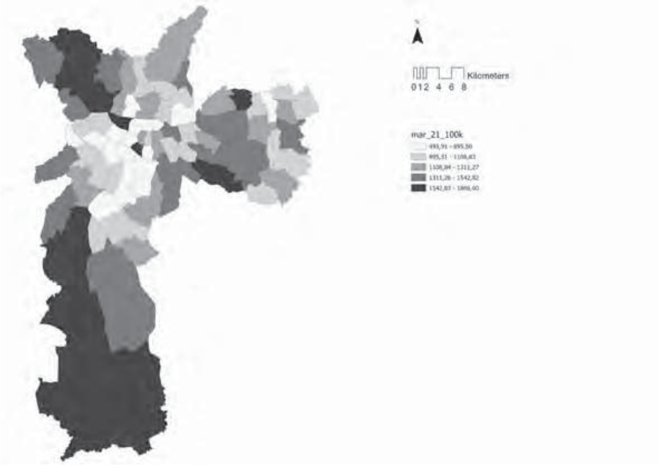








57	58
59	60
61	62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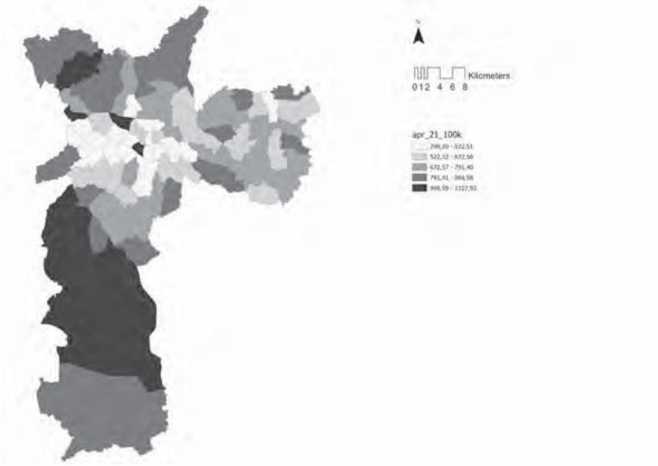
0 1 2 4 6 8
mar_21_100k


Kilometers
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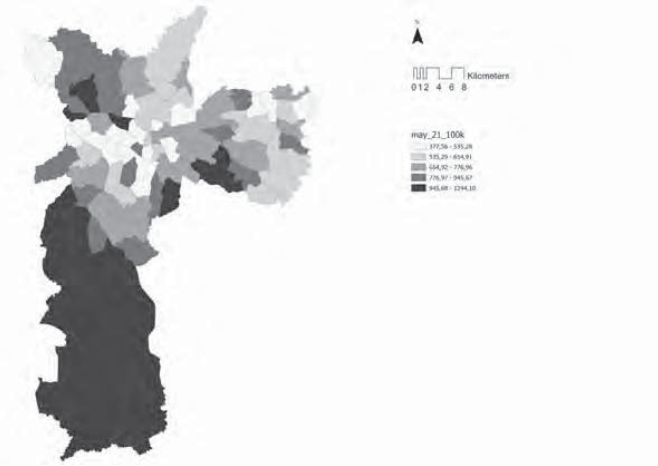
Kilometers
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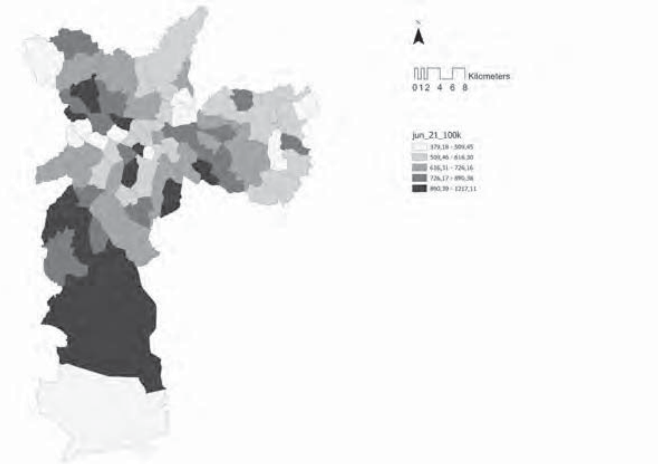
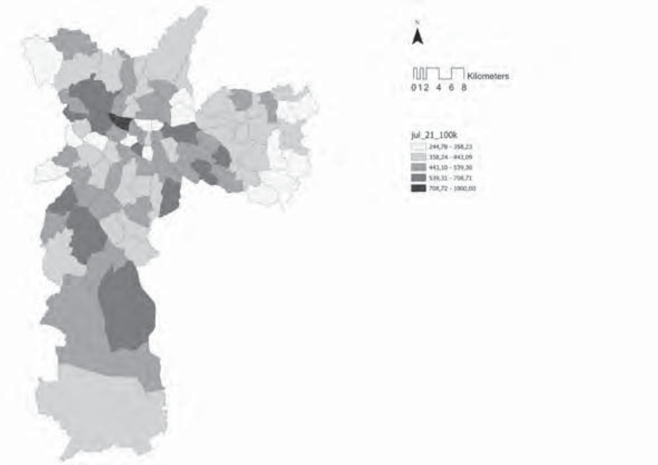
may_21_100k


Kilometers
0 1 2 4 6 8
jun_21_100k


Kilometers
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63	64
65	66
67	

the eastern zone, like *Sapopemba* and *Arcanduva*. From July to October (figs. 55 to 58), the general trend was declining, although never reaching zero-like figures. The pattern and distribution of cases remained relatively stable during this period, with a few variations.

The period between November and January (figs. 59 to 61) was characterised by an overall increase of cases citywide (from 60.888 to 97.459). The patterns we observe in this stage differ from the past ones to some extent. For instance, the extreme south areas, previously showing low relative rates, are now heavily impacted by the pandemic. There was once again a progressive redistribution of the cases from month to month; initially, the central areas were almost equally affected, whereas, at the end of the period, they were comparatively accounting for lower figures. This is even more evident in February (fig. 62) when the overall cases in Sao Paulo declined from 97.459 to 77.267.

In March 2021 (fig. 63), there was the absolute peak of cases citywide (as shown in fig. 50). The heterogeneity in the spatial distribution of cases, in this case, is quite striking. The entire south of Sao Paulo was heavily impacted, as well as the northwest and the eastern districts. The central areas, conversely, had proportionally significantly lower values, except for *Bela Vista.*

From April to July (figs. 64 to 67), the general trend was declining. The patterns observed for March were maintained rather constant throughout the following two months, with apparent disparities in rates between the central areas and the rest of the municipality, especially the entire south. Conversely, June and July displayed a shift towards the redistribution of the rates in a more homogenous scheme.

Conclusions and discussion: Reframing the analysis of Covid-19

Important insights emerged from this study. In the first place, it is clear how all case studies present what Cliff and Haggett (1984) defined as 'Type I' waves. In their work 'Islands epidemics' they suggested how, in large communities, waves are regular and continuous. This seems to be the case also for non-self-enclosed settlements. Moreover, they also pointed out how between peaks the number of cases never reaches zero. Indeed, the trend of the overall spread in the case studies – as well as the disaggregation to the sub-city level – alternates periods of great intensity followed by the so-called endemic periods, which never reach zero.

Relatedly, Cliff and Haggett (1984) show how epidemics tend to follow a 'hierarchical' pattern which varies depending on the size of the community. Although their analytical scale differs from the one employed here, we can see how, as they suggested, the spread seems to move from central areas to more peripheral units. These patterns were observed in all the instances selected for this study, although the shifts have different paces. Several hypotheses can be brought forward. For example, it might be possible that the virus initially spread in central areas due to a higher density of relations, activities and interactions. Then, with the implementation of lockdown measures, residents of the central areas significantly reduced their exposure to interactions, also because of the accessibility to services and jobs nearby, while commuters might have involuntarily been the means to bring the virus to external areas where also other issues, such as overcrowding (Patel *et al.*, 2020), might have favoured the spread of the pandemic more significantly than in central units. These hypotheses, therefore, should draw our attention to the density of interactions (rather than population density) and socio-spatial inequalities as a driver of the spread (Ribeiro *et al.*, 2021).

In this paper, we see also how different waves present different spatial patterns. Covid-19 hit cities differently across different periods. This finding acquires specific importance as it suggests that results coming from analysing only a portion of the outbreak might lead to very different conclusions compared to the analysis of the overall phenomenon. Hence, the research carried out in the past two years should be framed within the principle of partiality: to have a 'complete' picture, we need to put pieces together and relate findings in a framework that considers the spatiotemporal variability of the pandemic. From this perspective, it is then essential not only to observe what hierarchy is in place but to question what elements render the hierarchy such. How can we then explain the difference in spatial spread amongst the waves? What elements contribute to these changes? Although there is a plethora of potential explanations, here I argue for two possible interpretations.

On the one hand, behavioural changes might have played a crucial role in determining different spread patterns. This includes changes in travel and movement patterns. Rajput *et al.* (2022), for instance, examined the inter- and intra-borough movement for New York City in March and April 2020 using data sources relating to population density, aggregated population mobility, public rail transit use, car use, hotspot and non-hotspot movement patterns, and human activity agglomeration. The findings show that starting in mid-March, people's mobility in the city decreased by around 80%. Manhattan had the most significant disruption to both inter- and intra-borough traffic as a result of people working from home. Yet, due to people not commuting to Manhattan, the stay-at-home rules significantly increased population density (as they define it) in other peripheral units (such as Brooklyn and Queens). Although not examined in the study, it is possible that other mobility-related patterns emerged during the different phases of the pandemic.

On the other hand, changes in spread seem to coincide, unsurprisingly, with the implementation (and relaxation) of lockdown measures. However, a question remains: why are certain areas more affected than others when lockdowns are in place? Goldstein, Yeyati and Sartorio (2021) show that lockdowns' benefits fade with time as a result of the rising noncompliance with mobility limitations. This argument suggests that people living in more peripheral units might have been more exposed to contagion due to the necessity of travelling within the city to access basic services and jobs missing in their own neighbourhoods, even in periods of lockdowns. For instance, Li S.L. *et al.* (2021) found that in Sao Paulo the geographic variance in hospitalisation rates was driven by mobility and socioeconomic status, with low-income communities more likely to be fatally impacted by Covid-19.

All in all, this work showed how the spatiotemporal analysis of Covid-19 at a spatially granular scale can expand our understanding of the pandemic and shed light on the current debate about the variability of results across time and space. It also showed how cross-examining the spatial spread within cities can provide insights into the nature of the phenomenon and the socio-spatial components that acted as drivers of the pandemic, and that are yet to be ascertained.

Notes

1. As pointed out by Casti (2020), there may be significant differences in testing procedures and preventive or operational measures on disease containment. This has led some researchers to question the reliability of the data with respect to the true extent of the contagion and their use to derive quantitatively exact indicators. The same applies to the data used for this study.

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Appendix 1. Data sources

City	*Theme*	*Variable*	*Source*	*URL*
London	Covid-19	N° of cases	phe (Public Health of England)	https://coronavirus.data.gov.uk/details/download
	Statistical boundaries	msoas Boundaries	London Datastore	https://data.london.gov.uk/dataset/statistical-gis-boundary-files-london
	Demography	msoas population estimates	ons (Office for National statistics)	https://www.ons.gov.uk/peoplepopulationandcommunity
New York City	Covid-19	Case rates	nyc dohmh	https://github.com/nychealth/coronavirus-data
	Statistical boundaries	modzctas boundaries	nyc Open Data	https://data.cityofnewyork.us/Health/Modified-Zip-Code-Tabulation-Areas-MODZCTA-Map/5fzm-kpwv
	Demography	modzctas population estimates	u.s. Census Bureau	https://data.census.gov/cedsci/
Rome	Covid-19	Case rates	dep Lazio	Not available
	Statistical boundaries	boundaries	Roma Capitale Open Data	https://www.comune.roma.it/TERRITORIO/nic-gwt/
	Demography	zubs population estimates	istat	https://dati.istat.it/
Sao Paulo	Covid-19	N° of cases	tabnet - Citade de Sao Paulo Saude	https://www.prefeitura.sp.gov.br/cidade/secretarias/saude/tabnet/
	Statistical boundaries	msoas Boundaries	Prefeitura de Sao Paulo - Dados abertos	http://dados.prefeitura.sp.gov.br/
	Demography	msoas population estimates	Fundação seade	https://repositorio.seade.gov.br/