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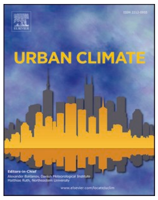

Frozen city: Analysing the disruption and resilience of urban activities during a heavy snowfall event using Google Popular Times

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ABSTRACT

Understanding the impact of climate change on cities is fundamental to address the increasing occurrence of extreme weather events. This research aims to raise awareness and emphasise the need and potential of proactive measures to mitigate the adverse effects of climate change. To do so, this article conducts a case study for a huge snowfall that occurred in the city of Madrid (Spain) in January 2021, blocking the city for several days. The analysis is based on geolocated big data sourced from Google Popular Times (GPT), which captures the occupancy of establishments throughout the city over the entire study period. An exploratory spatial-temporal analysis has been conducted to examine the impact of the snowfall on the daily activities of the city, taking into consideration the demographic characteristics. The findings reveal a distinction in the impact of the snowfall on activities. Essential activities experience less impact compared to leisure activities. Furthermore, at the socio-economic level, the impact on low-income neighbourhoods is observed to be less affected than on high-income neighbourhoods. The implications of this research contribute to the body of knowledge on climate change resilience and adaptation, providing valuable insights for urban management strategies and informing future research in this field.

1. Introduction

Climate change will transform life on Earth in ways unseen by contemporary societies. Its effects include a higher frequency and intensity of temperature extremes, as well as precipitation values, which lead to situations like heat waves, floods, droughts, hurricanes, dust storms and wildfires (Stott, 2016). Research is still necessary to understand these effects within cities, where over half of the world's population lives today. Besides the impact of extreme weather events on the environment and public health (De Sario et al., 2013), the disruption of urban activities and the economic losses related are huge.

The economic losses of extreme climate events include physical damage to all types of buildings, material assess within buildings,

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public infrastructure, vehicles, agriculture assets –crops, livestock, and timber–, among others. Economic losses due to business interruption can be significant too. Only in the USA and in 2021, twenty weather and climate extreme events caused a total cost of $145 billion (NOAA National Centers for Environmental Information (NCEI), 2023). In the European Union, these events caused economic losses estimated at EUR 560 billion between 1980 and 2021, of which EUR 56.6 billion only in the last year (2021) (European Environment Agency, 2023). The fact that between only one quarter and one third of these losses were insured (European Environment Agency, 2022) confirm that much can be done to adapt our environments and anticipate or mitigate the effects of these events.

While it is true that global warming is reducing the overall frequency of precipitation, we are witnessing an increasing number and intensity of heavy precipitation events. Indeed, rising temperatures may reduce the total amount of snowfall and snow cover (Brutel-Vuilmet et al., 2013), with important environmental and economic effects (Wu et al., 2021), but they can also result in changes in atmospheric moisture and the formation of more intense weather systems. These changes could increase the likelihood of extreme snowfall events in mid-latitudes as a result of more variable and disruptive climate patterns associated with climate change (Faranda, 2020).

The data observed confirm this increase, which has been taking place since the 1950s, and it is "very likely" that heavy precipitation events will be more intense and frequent with global warming: for each Celsius degree, 7% more intense and 50% more frequent (Masson-Delmotte et al., 2021). Whereas climate change is reducing the spatial extent of snow cover in the Northern Hemisphere, especially at lower altitudes, the probability of changing patterns in snowfall events and snow cover has a great spatial variability. For example, decreasing in Britain (Bell et al., 2016), Canada's Columbia Mountains (Mortezapour et al., 2022), or the Upper Indus (Romshoo and Marazi, 2022); decreasing or increasing at different elevations of the Pyrenees (López-Moreno et al., 2011), or different areas of Estonia (Jaagus, 1997); and increasing in the northern part of Japan Alps and Hokkaido (Ohba and Sugimoto, 2020) or the Balkans (Faranda, 2020).

Heavy snowfall events can cause a great disruption in cities for a number of reasons. First, the impact of a snowfall event can be sudden, in just a few hours. Second, snow becomes a physical obstacle for both pedestrians and traffic, and it eventually affects all types of movement within the city. Third, snow can damage power towers and lines, causing electrical breakdowns and blackouts (Ohba and Sugimoto, 2020), and thus a collapse of electricity-dependent human activities. In sum, heavy snowfall events can potentially disrupt all activities in cities.

Integrating new perspectives on methods to measure the impacts of extreme weather events on urban activity resilience is necessary and possible. Urban resilience is the capacity of an urban system and all its constituent socioecological and sociotechnical networks across temporal and spatial scales to maintain or rapidly return to desired functions in the face of disruption, adapt to change, and transform systems that limit current or future adaptive capacity (Meerow et al., 2016). Starting from this wide definition, and following the global impact of the pandemic, a series of studies have been conducted to evaluate resilience in various urban aspects. In the specific context of Spanish cities, the resilience of the tourism sector has been examined using hotel tourist demand as an indicator, specifically the number of registered overnight stays (Duro et al., 2022). Additionally, research has focused on analysing the resilience of food and beverage establishments, investigating how those adopting home delivery platforms achieved greater adaptive capacity during the pandemic (Wang et al., 2022). Furthermore, surveys have been conducted targeting hospitality establishments in Germany to examine the sector's response to the COVID-19 pandemic and identify determining factors influencing differential resilience of these establishments (Neise et al., 2021).

The objective of this paper is to present a new perspective quantify and measure the level of disruption and resilience in urban activity participation during a heavy snowfall event. This analysis will utilize newly available location-based big data and provide rich spatial details at the intraurban scale, disaggregated by activity category. We use the case of the city of Madrid, where a chaotic situation followed the great snowfall of Storm Filomena in January 2021. The snowfall reached up to 60 cm (24 in), killed at least two people, and blocked all transportation and the access to key facilities such as hospitals.

To the best of our knowledge, this is the first study providing such a detailed spatial-temporal, quantitative, and multisector analysis at the intra-urban scale. This task has been now possible thanks to the availability of emerging big data sources that offer the real-time busyness of commercial Points of Interest (POIs) such as shops or bars. In this paper, we explore the usefulness of Google Maps' POIs and Google Popular Times (GPT) in monitoring and measuring the disruption and recovery processes of urban activities during the aforementioned unprecedented snowfall. Google Places Points of Interest (POIs) are currently one of the most comprehensive POI databases containing land use attributes of a city, because data are disaggregated at the level of individual venues, providing its precise location, and activity category. In addition, a fuller picture of POI information includes opening hours and occupation rate with the emergence of Google Popular Times (GPT). The data enables us to conduct a detailed spatiotemporal description of urban activities. We can monitor the urban activities and compare them against the previous records, which in the future could be used as an early warning of changing trends. In this paper, we therefore propose this novel data utilisation to understand the disruption and resilience of urban activities during the heavy snowfall in Madrid.

The remainder of this paper is organised as follows. Section 2 reviews the studies regarding the impact of snowfall disasters on societies and the existing geospatial tools to measure such impacts. Section 3 describes the new GPT data and the methodology used for the spatial analysis of this paper, followed by the case study during the heavy snowfall in Madrid. We illustrate the different disruption and resilience patterns for different activity types and social groups. Section 5 contains the discussion and the conclusion of this study and future research directions can be found in Section 6.

2. Background

2.1. Studying cities under the snow

"By introducing snow or ice into an urban setting with hypersensitive movement patterns, any form of chaos may be precipitated" (Rooney, 1967).

Extreme snowfall causes great physical and economic losses, inconveniences, and costs, from snow removal to operations and rebuilding infrastructure. Snow accumulation can potentially disrupt or interrupt most of the mobility and activities in cities, either directly or indirectly (Ohba and Sugimoto, 2020). The economic losses due to business interruption can be larger than those related to damaged buildings, infrastructure or other assets.

The average economic cost of each winter storm event in the USA has been estimated in about $4.4 billion (NOAA National Centers for Environmental Information (NCEI), 2023), but could be much higher. For example, the historic cold wave and winter storm that occurred from Nebraska to Texas in February 2021 costed $24 billion and 226 human lives.

The previous approach to this topic lacks the necessary detail to address inner urban inequalities of all sorts, following now old references like Rooney Rooney (1967) and De Freitas De Freitas (1975), who aimed at estimating the general, citywide impact of these events on human activity by looking at correlations with snowfall properties (depth, rate, and duration of the snowfall, wind speed, etc.). As a result, meteorological conditions were the only independent variables used for a better risk consideration, anticipation, and mitigation measures; perhaps because of the lack of disaggregated quantitative data at the intraurban scale to describe the level of disruption of urban activities. Only some data could be considered for the purposes of building continuous variables for some specific urban dynamics, e.g. parking-meter revenue data (Rooney, 1967).

While more recent literature has underscored the necessary focus on cities to analyse the impact of cold waves and extreme snowfall (Jahn, 2015), empirical analysis based on newly available data sources have kept a citywide approach (Freeman, 2011; Wang and Taylor, 2015). In turn, other researchers have analysed the impact of snowfall events at larger or smaller scales of analysis, like the regional scale (Schmidlin, 1990; Squires et al., 2014), that of key locations like airports (Cerruti and Decker, 2011), or that of specific urban systems like the road network (Jenelius and Mattsson, 2012).

The intra-urban analysis of the impact of extreme snowfalls based on new geolocated data is not only necessary, but also possible as proved by studies like Hong et al. (2021) –who used smartphone data to analyse the inequality of community resilience within Houston, Texas, during Hurricane Harvey in 2017–, and Kryvasheyeu et al. (2023) –who used Twitter data to assess disaster damage at the intra-urban scale of fifty US metropolitan areas during Hurricane Sandy in 2012.

2.2. The potential of georeferenced big data to evaluate the impact on urban activities

Previous studies have been constrained by the lack of data to estimate the effects of snowfall events at the intra-urban scale. Relying on the quality and extension of media coverage, the content analysis of newspapers constituted the only method in the literature until recently (Cerruti and Decker, 2011), providing a citywide general description. As a result, researchers have not been able to provide a detailed, reliable quantitative analysis, and the spatial disaggregation at the intraurban level was unfeasible.

However, we have witnessed a technological and digital revolution in our cities during the last couple of decades. Contemporary cities integrate countless sensors of diverse types, which collect big volumes of georeferenced data rapidly and at low costs ('big data') to support improved urban analysis, the management of resources, service operation, the anticipation of changing trends, etc. (Ratti and Claudel, 2016). Georeferenced big data can support a more detailed spatial analysis and real-time monitoring, with a fine granularity often unseen in previous literature for certain topics.

Many environmental data can be collected and analysed spatially, making it possible to monitor the situations and answer the questions relevant to urban sustainability, e.g. greenhouse gas emissions, identifying and foreseeing more urban threats (Lorenzo-Sáez et al., 2022; Shi et al., 2021; Xie and Sun, 2021; Xu et al., 2023). Likewise, many human activities in urban areas are monitored by a diversity of sensors, so it is possible to quantify the disruption caused by any event, as well as the resilience and recovery in the following days and weeks. Google Places points of interest (POI) data provides rich information on land use attributes and enable urban studies to learn the spatial relationship between urban issues and land use attributes (Deng and Newsam, 2017; Lu et al., 2018; Yao et al., 2017, Bernabéu-Bautista et al., 2023). Previous literature has used Google POIs to analyse land use distributions (Deng and Newsam, 2017; Yao et al., 2017) –even at the scale of individual buildings (Lin et al., 2021)–, to forecast mobility purposes (Cui et al., 2018), and to predict NO_2 concentrations (Lu et al., 2018).

However, the existence of a POI is static, and this POI data does not allow one to conduct in-depth temporal analysis. Recently, Google Popular Times (GPT) drastically change the situation. Google Popular Times are aggregated and anonymized by Google using the data of people who have opted in to Google Location History (Google, 2020). GPT show the busyness of a venue and are available at some specific places and specific times, so time-varying levels of activity demand can be deduced considering the activity type associate with the POI having GPT data. A number of studies have noticed and illustrated the usefulness of this GPT information. Mahajan et al. (2021) analysed the demand patterns of urban activities during COVID-19 lockdowns in Munich using GPT data. More specifically, they used the GPT data of supermarkets, chemist shops, and fast-food restaurants. Vitello et al. (2023) used GPT data of transit stations to predict the station's passenger demand. Vongvanich et al., (2023) explained and predicted the GPT of railway stations using the GPT of nearby GPT of other POI types. Namely, they tried to model the station demand by using other urban activities near a station. Their findings encourage us to explore the spatial-temporal patterns of urban activities using this opportunistic data.

2.3. Storm Filomena in Madrid

As a case study, this research has taken the extraordinary case of Storm Filomena, which arrived in the city of Madrid (Spain) on Thursday, the 7th of January 2021, but intensified throughout the two following days. This event not only was uncommon and extreme, but also had a huge effect on urban activities: Madrid is a capital city of over three million inhabitants, unprepared for this type of snowfall events, which are rare in Mediterranean climates. Further, South European countries are among the most vulnerable to climate change. The large extent and diversity of the urban activity areas affected make Madrid during Storm Filomena a unique case study to prepare the ground for further research.

Heavy snowfall events are generally uncommon in non-mountainous areas of the Iberian Peninsula. Thus, although snow is not rare in the mountains near Madrid (Gascón et al., 2015), the city of Madrid is hardly covered by snow, with an average of 3.8 days per year in the last century (Pérez González et al., 2022), among other factors due to urban effects like the heat island (Zenner, 2016).

The great snowfall event resulted from Storm Filomena formed over the Atlantic Ocean, advancing from the south-west and colliding with cold air channelled from the Arctic, and was the heaviest snowfall recorded in Madrid since 1971. While typical average lowest temperatures in winter are between 0.2 and 3.7 degrees, Filomena's snowfall resulted in surface temperatures between −13 and − 2.5 degrees. An anticyclone following Filomena helped to keep the snow accumulation of up to 53 cm high for ten days (Pérez González et al., 2022).

According to the categorization of disruptions in the revised literature, Filomena's effects must be considered a "first order" and "paralyzing" disruption in the majority of activities (De Freitas, 1975): urban road transportation (near absence of moving vehicles and many stalled vehicles), retail trade (many establishments closed), postponements of events, education (many schools closed), rail and air traffic (Fig. 1). Only communications and power facilities were not significantly affected.

The situation was described as an "unacceptable chaos" by the media even one week after the snow started to fall.[1] Snow in Madrid city is not common, so buildings, public spaces, and services are rarely prepared for snowfall events, not to mention the lack of snow control and removal technologies. Six days after the start of the snowfall, about 90% of roads remained affected; 12 days later, the situation was still problematic on 43% of roads.[2] Special mention must be made of vegetation: 11% of the winter plant cover was damaged, as many trees in Madrid belong to Mediterranean climates and are not naturally prepared for such storms (Pérez González et al., 2022). Many trees and countless branches fell down, worsening the blockage of roads and streets.

According to a newspaper report based on mobile-phone big data, in the first couple of days after the storm, mobility patterns decreased to the low levels experienced in March 2020 during the first weeks of extreme, home-based lockdown due to the Covid-19 pandemic: a 65% reduction of total trips on the first Monday after the storm. It took two weeks to return to normal in terms of mobility patterns.[3]

Fig. 1. Total disruption of traffic on Madrid's M-30, main ring motorway. Source: authors.

[1] https://elpais.com/opinion/2021-01-15/filomena-pesima-gestion.html (last accessed date: 03-24-2023)
[2] https://elpais.com/espana/madrid/2021-01-19/el-43-de-las-calles-de-madrid-sigue-sin-estar-despejado-10-dias-despues-de-la-nevada.html (last accessed date: 03-24-2023)
[3] https://elpais.com/espana/madrid/2021-02-12/asi-congelo-madrid-filomena-hasta-un-80-menos-de-movimientos-y-dos-semanas-para-recuperar-la-normalidad.html?prm=copy_link (last accessed date: 03-24-2023)

3. Materials and methods

3.1. Data: Google places - points of interest (POIs)

The data used in this paper were obtained from Google Places API and Google Popular Times webpages through a downloading process in Python. Firstly, the POIs are obtained using Google Places API to create a POI database, which is a one-time effort. Secondly, GPT data is obtained with web crawler using name and address of the obtained Google POIs. Using Google Place to create such a POI database can guarantee a high matching rate in the web crawler processing. One can also use Foursquare or OpenStreetMap to create this POI database. The data set is made up of the POIs that broadcasted "live" (active) in the municipality of Madrid during the week of December prior to the start of the Christmas holidays and until mid-February (from 14 December to 15 February 2021). The weeks prior to Filomena and the weeks of recovery from normality after the event are thus included.

For this study, the data from 4277 Points of Interest (POIs) located within the municipality of Madrid (Fig. 3) were utilized, which were live-streaming at some point during the study period. GPT combines various data from the Google location histories to provide insights about the popularity of the places. As a result, data on the number of visitors and the length of their visits can be linked with user reviews and other information (e.g., the type of the place) from third-party sources (Google, 2020). However, GPT cannot indicate the actual number of visitors, and the sampling bias may be an issue because the collection of the data is based on using smartphones (Möhring et al., 2021). In our case, the data downloaded have been the name and type of POI, the address, number and rating of opinions, average occupancy history, the time users spend at the POI and the POI's occupancy at the time of download. The latter datum is only available for POIs broadcasting "live" from GPT. All POIs are geolocated with latitude and longitude coordinates and have been incorporated into a GIS, in this case QGIS. Fig. 2 shows the activity profile of a premises, with its historical occupations (in blue) and the "live" occupation at the time of downloading (in red).

Table 1 above displays an example of data downloaded from Google Popular Times. Table 2 below shows the number of POIs for each category, as well as the mean occupancy and its standard deviation across the entire analysed time period, and the mean occupancy and its standard deviation during the reference week used throughout the study, which corresponds to the second week of February.

3.2. Time period

Activity at POIs has been temporarily added on a weekly basis. In total, seven weeks have been considered:

- The week before Christmas (from 14 to 20 December 2020). We have excluded the period of the Christmas holidays from the analysis, as it is an atypical moment, but we include this week as the week before the storm. This was a week of strong activity, which was also conditioned by COVID-19.
- The second week of January 2021 (from 4 to 10). This includes the last Christmas holidays (Epiphany, an important local festivity in Madrid) and the days starting from 7 January and with the greatest snowfall intensity.
- The third week of January 2021 (from 11 to 17). Although the snowfall ended on the 10th, this was the week with the greatest impact, due to the accumulation of snow in the streets and the low temperatures. It coincided with a usual period of high activity in Madrid, related to returns and exchanges after Christmas and with the "sales" period.
- The fourth week of January 2021 (from 18 to 24), the fifth of January 2021 (from 25 to 31) and the first of February 2021 (from 2 to 7). These were weeks of recovery of normal activity after the snowfall.
- The week from 8 to 14 February 2021. This was marked by a situation of complete normality. This week has been taken as the reference week for the evaluation of the impacts of the storm.

For each week, the number of active POIs, which have broadcast live on at least one day of that week, and the average occupancy

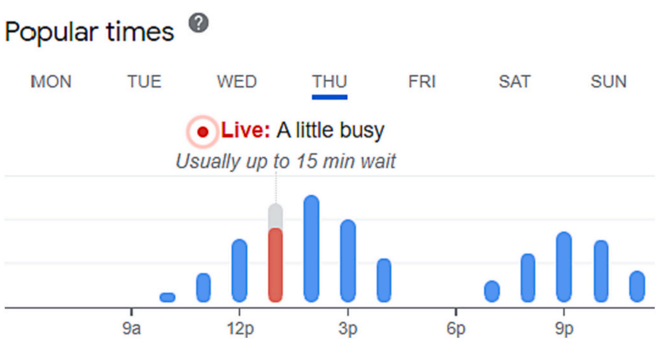


Fig. 2. Google Places and Google Popular Times information. The historical occupancy data are in blue, the occupancy at the time of the download in red. Source: Image obtained by searching for a POI on the Google website. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

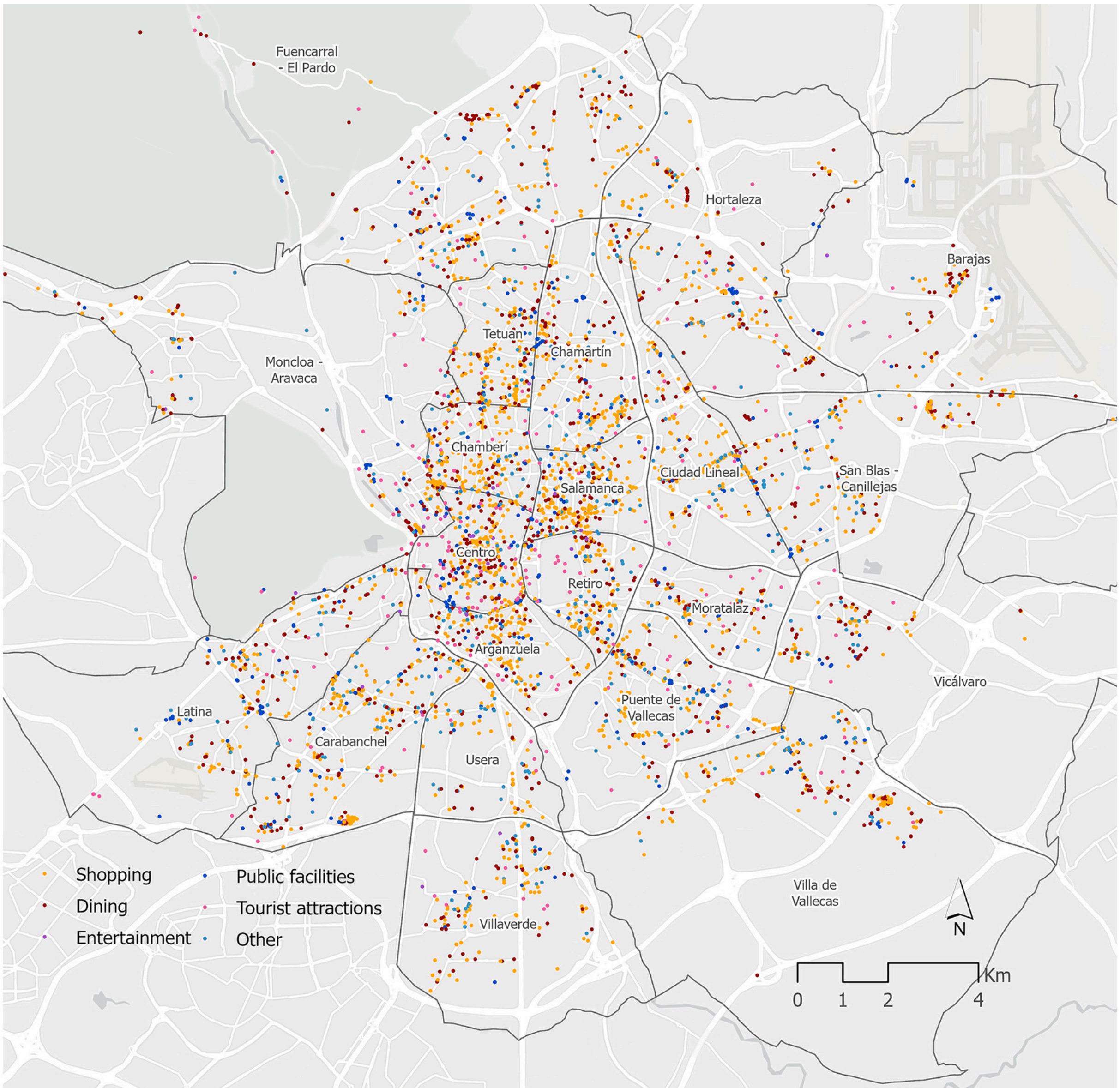


Fig. 3. POIs within the municipality of Madrid, classified by categories. Source: Own elaboration from Google Places – Google Popular Times.

Table 1
Google Popular Time data example. Source: Own elaboration from Google Places – Google Popular Times.

Date and time	2021-01-10 14:08:49
Name	El Palacio del Pollo
Latitude	40.3965703
Longitude	−3.6634643
POI type	restaurant
Address	Calle del Puerto Canfranc, 14, Madrid
Historical average	18
Live popularity	75
Rating score	4.7
Number of ratings	438
Average Time spent (min)	15

Table 2
Characteristics of the categories. Source: Own elaboration from Google Places – Google Popular Times.

Category	Number POIs	Average occupancy	Standard deviation	Average occupancy - reference week	Standard deviation – reference week
Dining	1042	22.67	11.39	26.17	21.25
Entertainment	36	18.81	12.16	20.15	19.28
Tourist attractions	239	21.24	14.62	27.17	19.54
Public facilities	407	31.03	15.91	39	33.29
Shopping	1988	31.96	13.05	33.49	18.23
Other	565	30.51	12.14	36.94	25.22

they have had, have been calculated. Index numbers have also been obtained for these two variables, the reference week being given the value 100. In this way it is possible to assess the impact of the drop in activity and the rate of recovery. These indicators have been calculated for the total POI and for each of the six categories in which they have been grouped.

3.3. Spatial analysis

The spatial differences in the drop and recovery of activity have been analysed with Kernel density maps and interpolations of the occupancy level of the premises using the ArcGIS Pro software.

- *Kernel density*. Calculated for each of the weeks analysed using cells with a resolution of 100 × 100 meters and densities within a 500 m-distance from each cell. Densities are obtained for the number of active POIs weighted by their average occupancy level. Density values are given per hectare.
- *Interpolations of the occupancy level*. From the average occupancy levels of each POI, a raster surface of the occupancy level in the city has been obtained. An inverse distance weighting technique has been used, with a variable search radius and squaring the distance.

The maps have been obtained for each week and for the six POI categories. This article presents the results for the total POIs and the cartographic analysis contains those for the Dining and Shopping categories. These are the two categories with the highest number of POIs and the ones with the behaviour that is most differentiated from each other. While Shopping is a basic and necessary activity (stocking up on food), Dining away from home is something optional and essentially avoidable in a situation such as a heavy snowfall.

3.4. Cluster analysis: Impacts according to types of neighbourhoods

The drop in activity as a consequence of the storm is analysed at the level of administrative units, using the neighbourhoods of the city of Madrid. A typology is used for the 128 neighbourhoods of the city, classified according to their income level and distance from the city centre (Puerta del Sol square). The income data have been obtained from the official website of the National Institute of Statistics.[4] The typology of neighbourhoods has been carried out with a K-means clustering for identifying the clusters. The data have previously been normalised, their ranges being rescaled to a scale from 0 to 1. The optimal number of groups has been chosen using the "elbow point" rule. A total of five groups have been defined (Fig. 4 and its Table 3).

The five established groups are characterised by:

- Neighbourhoods in the centre of the city centre, at a short distance from the city centre. Two groups are differentiated according to their income level: medium (Medium-income central) and high (High-income central). These are groups with a high POI density.
- Low-income neighbourhoods and mostly central location (Low-income central). This is a group of highly residential neighbourhoods, with a lower density of premises per inhabitant.
- Neighbourhoods on the urban periphery, far from the centre. In general, these are spaces of a more residential nature and a lower POI density. They have differentiated incomes, low (Low-income outskirts) and high (High-income outskirts).

The impact of the snowfall according to types of neighbourhoods has been carried out for the total POIs, and for the categories of Shopping and Dining. This allows to analyses the drop and rates of recovery according to types of neighbourhoods in essential and less essential activities.

Working with administrative units is of great interest from the perspective of snowfall prevention and management and other extreme events, as these are the units with which local administration technicians' work, with implications for a more effective governance. Moreover, their centrality and socio-economic level makes it possible to characterise each context, improving the prevention and management of events.

[4] https://www.ine.es/jaxiT3/Tabla.htm?t=31097 (last accessed date: 05-23-2023)

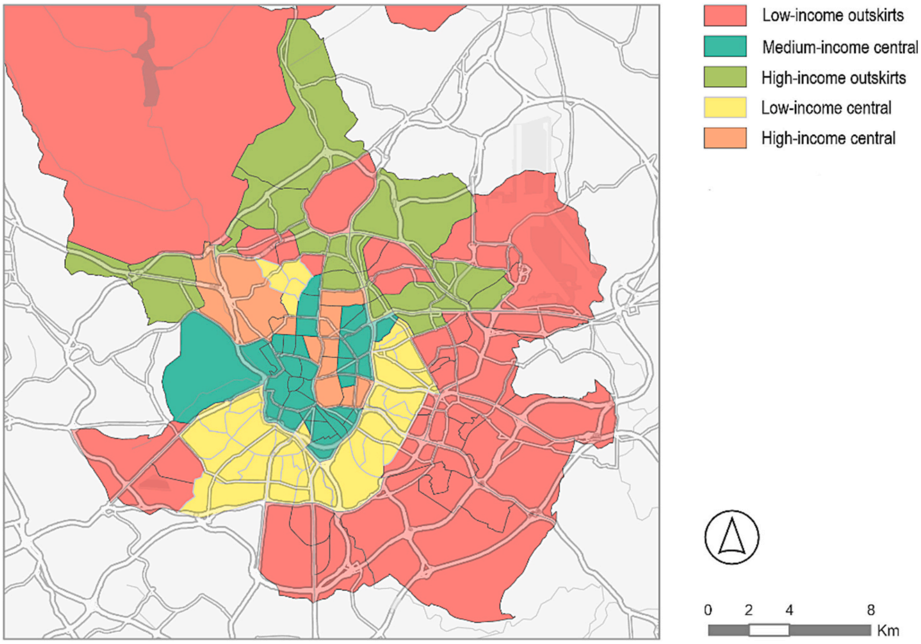


Fig. 4. Classification of neighbourhoods according to income levels and distance to the centre. Source: Own elaboration

Table 3
Characteristics of the cluster groups created. Source: Own elaboration from Google Places – Google Popular Times.

Group	Total population	Onlive POI average number	POI density (per 1000 inhabitants)	Income		Distance to the centre	
				Average	St. Dev.	Average	St. Dev.
Medium-income central (blue)	726,307	1203	1.66	46,083	6374	2309	1271
High-income central (orange)	182,831	351	1.92	72,023	7243	2800	1073
Low-income semi-peripherals (yellow)	1,127,201	1065	0.94	30,114	4050	4385	1016
Low-income outskirts (red)	940,819	1207	1.28	34,522	7082	7849	1480
High-income outskirts (green)	335,152	451	1.35	71,059	12,853	7555	1667
Total	3,312,310	4277	1.29	44,194	17,360	5180	2642

4. Results

4.1. General drop in activity

Table 4 shows the evolution of the number of active POIs and their average occupancy in each of the analysis weeks. In the reference week of February, the total number of active POIs was just over 3400, with an average occupancy of 41%. These values are lower than those registered in the week before Christmas, when leisure and consumption traditionally grow in Madrid (José Carpio-Pinedo et al., 2022).

Table 4
Total number of POIs broadcasting live at least one day of the study week and their average occupancy. Source: Own elaboration from Google Places – Google Popular Times.

	Number of POIs broadcasting live			Average occupancy		
Weeks	Total	Difference from 2nd week of February	2nd week of February = 100	Percentage	Difference from 2nd week of February	2nd week of February = 100
12/14–12/20	3795	378	111.06	43.14	2.40	105.88
01/04–01/10	3593	176	105.15	33.30	−7.44	81.73
01/11–01/17	3629	212	106.20	25.20	−15.55	61.85
01/18–01/24	2759	−658	80.74	32.97	−7.77	80.92
01/25–01/31	3313	−104	96.96	37.96	−2.78	93.17
02/01–02/07	3326	−91	97.34	39.43	−1.32	96.77
02/08–02/14 (RW)	3417	0	100.00	40.75	0.00	100.00

Storm Filomena resulted in a sharp drop (−18%) in average occupancy as early as in the first week of January (from January 4 to 10), as a consequence of the heavy snowfall at the end of this week. The following week registers the lowest occupancy point, because of the snow piled up in the streets and boosted by the cold wave that took place from 10 to 17 January. From the week of 18 January, occupancy levels started to recover.

The behaviour of the number of active POIs was different from that of occupancy: while occupancy dropped with the snowfall, the number of active POIs initially remained high. These were Christmas end and sales weeks, which kept premises open, but at very low occupancy levels. However, after those two weeks, as of January 18, the lowest number of active POIs was recorded, with a drop of 19%. The snowfall and the low occupancy of the previous weeks, compounded by the third COVID-19 wave that affected Madrid those days with an increase in infections, explains the temporary closure of many activities. In any case, the impact on active POIs was much less than on occupancy levels, and their recovery was also faster. Thus, while in the last week of January 97% of the POIs were already active, that week only 93% of the average occupancy had been recovered in relation to the reference week of February.

4.2. *Analysis according to activity types*

The drop in activity varied considerably according to the types of activities involved. The drop was lower and the rate of recovery was faster in those activities that were most relevant to the population, such as public facilities and shopping. In contrast, optional and non-essential activities such as tourist attractions, entertainment or dining experienced a sharp drop and a slower recovery rate.

These differences are highly observable if we compare the Shopping activities, which encompass all types of businesses, from bakeries, clothing stores, furniture, to supermarkets (representing 48% of the total POIs considered) with Dining, which includes bars, restaurants, and cafeterias (24% of the total POIs). In Shopping, the impact of Filomena was lower: the number of active POIs showed little variation, with a drop of 11.5% in the third week of January, while the second week of January was marked by a slight increase coinciding with the start of the sales. On the contrary, the Dining venues experienced a much greater impact. During the week before Christmas, there were 29% more active POIs, but there was a 39% drop during the third week of January (Fig. 5, left).

The same goes for occupancy (Fig. 5, right). Shopping decreased 25% in the second week of January, while in “Dining” occupancy fell to above 50%. In addition, occupancy recovery rates are very different between categories. In the week of January 18, Shopping occupancy was already 95% compared to the reference week of February and practically 100% in the week of January 25. On the contrary, during those weeks Dining occupancy was 60% and 80% respectively.

4.3. *Spatial distribution of the drop in activity*

Fig. 6 shows the density of premises weighted by their occupancy during the weeks analysed. During a regular period in Madrid, the highest densities were located in the city centre and the main commercial hubs. With the snowfall, the drops equally affected the city as a whole, meaning that the densities dropped sharply both in the densest areas of the centre and in the areas with the highest density on the periphery. In fact, the coefficient of variation in the distribution of density was very similar throughout all the weeks (Table 5), showing a similar drop in activity in the city as a whole.

However, differences appear when we analyse the spatial distribution of the snowfall impact according to categories, especially if we take the shopping and dining categories as a reference (Figs. 7 and 8). The impact of the snowfall on activity in the dining category was much stronger, which in this case translated into drops in average densities of up to 55%, compared to 20% in Shopping. In Shopping, the drops were very homogeneous in the municipality as a whole, with coefficients of variation (CV) that remained stable throughout the period. Only in the weeks before Christmas and the subsequent sales did activity intensify in the areas with the highest

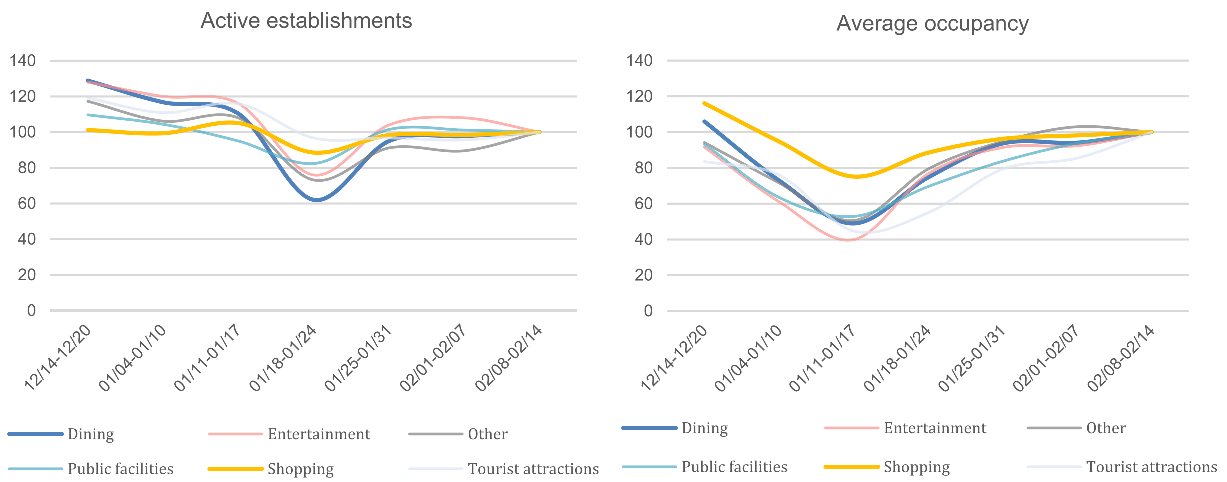


Fig. 5. Active establishments (left) and average occupancy (right) according to major types of activity. Second week of February equals 100. Source: Own elaboration from Google Places – Google Popular Times.

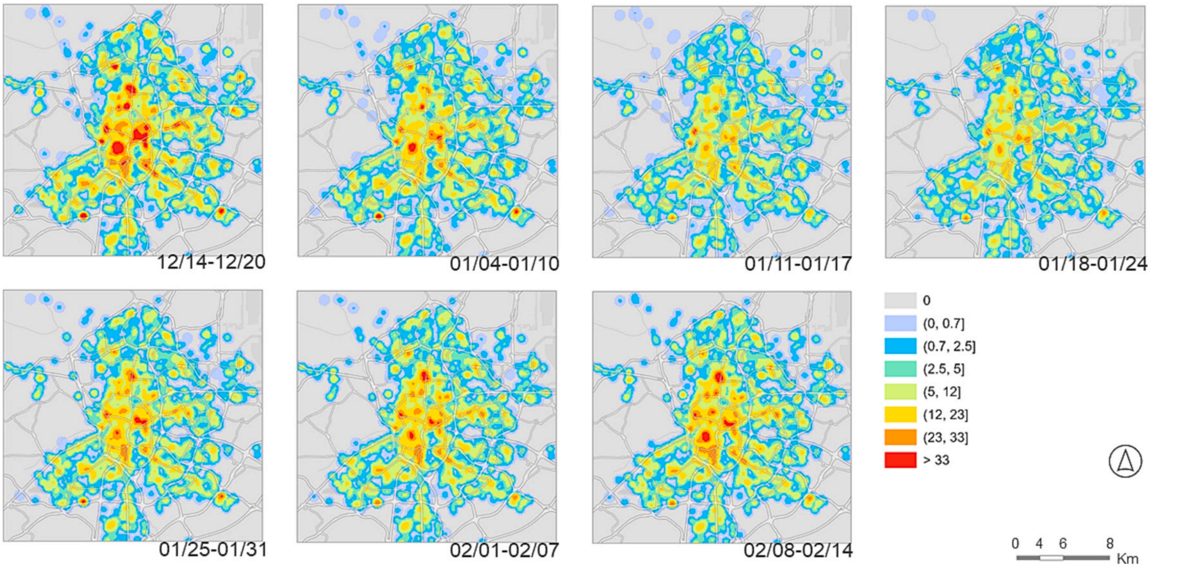


Fig. 6. Kernel density of the total number of POIs/Ha broadcasting live weighted by average occupancy, for each one of the weeks. Source: Own elaboration from Google Places – Google Popular Times.

Table 5
Descriptive statistics of the distribution of the density of active POI/Ha weighted by their activity. Source: Own elaboration from Google Places – Google Popular Times.

Weeks	TOTAL			SHOPPING			DINING		
	Average	St. Dev.	CV	Average	St. Dev.	CV	Average	St. Dev.	C.V.
12/14–12/20	3.39	6.61	195.3	1.64	3.69	224.5	0.70	1.53	218.4
01/04–01/10	2.47	4.79	193.8	1.32	2.94	223.2	0.43	0.96	220.9
01/11–01/17	1.93	3.72	192.6	1.12	2.42	215.3	0.29	0.68	235.1
01/18–01/24	1.87	3.62	193.4	1.09	2.35	215.5	0.23	0.57	246.9
01/25–01/31	2.58	4.91	190.0	1.31	2.83	215.3	0.45	1.02	226.9
02/01–02/07	2.69	5.09	189.3	1.33	2.86	214.5	0.47	1.04	222.3
02/08–02/14 (**RW**)	2.85	5.43	190.5	1.38	2.97	215.6	0.52	1.15	223.7

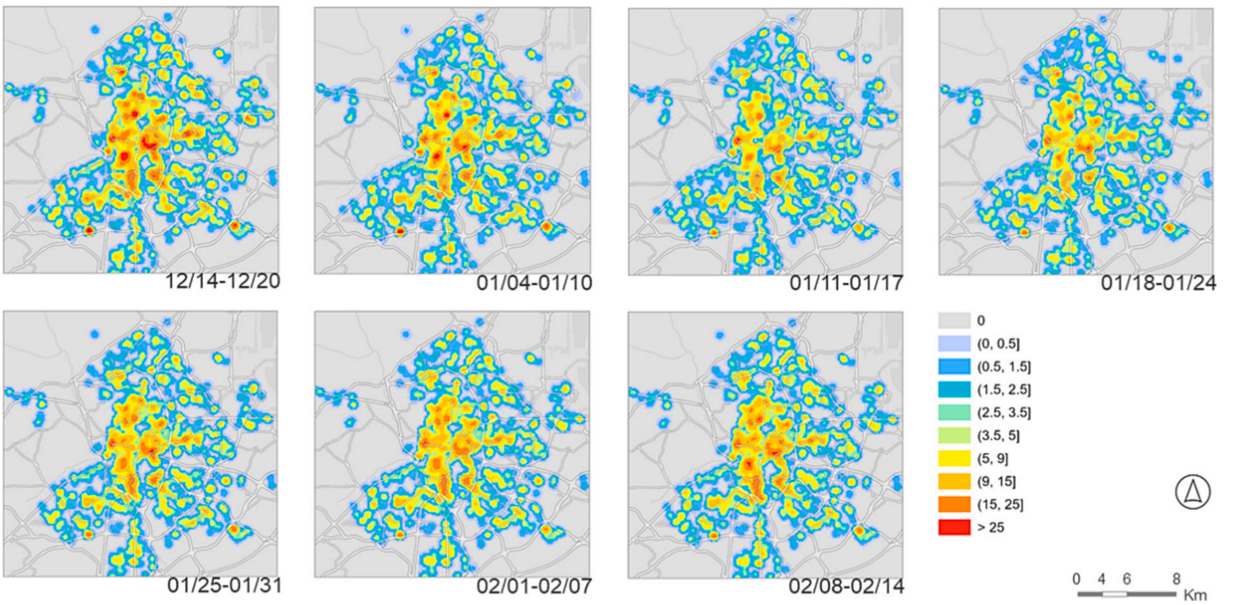


Fig. 7. Kernel densities of the number of POI/Ha broadcasting live weighted by the average occupancy of the "Shopping" category, for each of the weeks in the 2020–2021 period. Source: Own elaboration from Google Places – Google Popular Times.

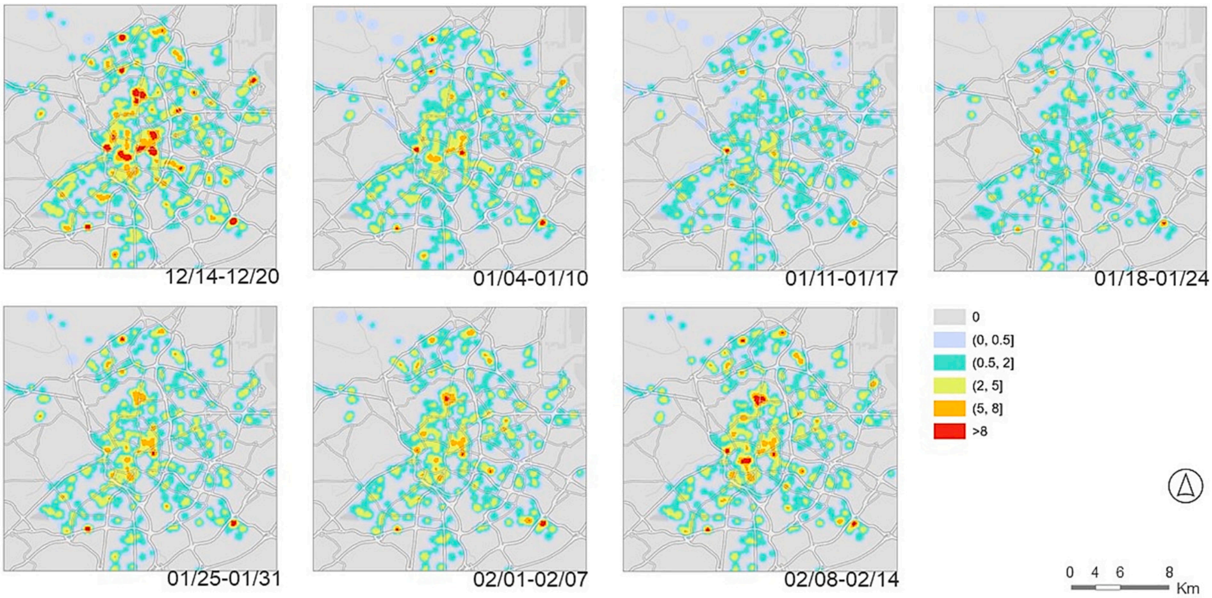


Fig. 8. Kernel densities of the number of POI/Ha broadcasting live weighted by the average occupancy of the "Dining" category, for each of the weeks in the 2020–2021 period. Source: Own elaboration from Google Places – Google Popular Times.

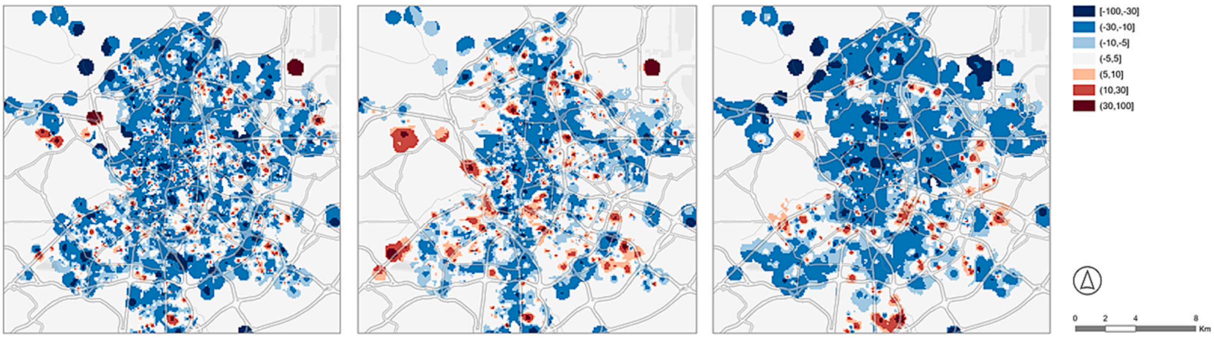


Fig. 9. Differences with respect to the second week of February in the period 2020–2021 of the second week of January. From left to right, they correspond to "Total", "Shopping" and "Dining". Source: Own elaboration from Google Places – Google Popular Times.

density (highest CVs, Table 5). These "hot" areas of the centre of the municipality in the first two weeks "cooled" with the snowfall. Meanwhile, dining activity was reduced very markedly in the city centre areas, which are usually those with the highest activity. This, however, does not translate into a more homogeneous distribution of density (lower CVs). On the contrary, the densities have a more unequal spatial distribution during the snowfall weeks. What explains this is that, with activity practically closed, the premises that remained open created a spattering of higher-density small areas that increased inequality in density distribution (Fig. 8 and Table 5).

In order to see the distribution of the differences with respect to the second week of February, an IDW has been carried out of all the POIs that broadcasted live weighted by their occupation. On the basis of this, the difference with respect to the second week of February has been calculated and mapped. The results have been obtained for all the study weeks in the period 2020–2021. Fig. 9 shows the second week of February, which was noted for the greatest impact in terms of occupancy.

4.4. Differences according to types of neighbourhoods

The differences in the total number of active POIs, depending on the type of neighbourhood, are small. There was a slightly smaller drop among the most central groups, but without differences according to income levels (Fig. 10, top). However, there do seem to be marked differences in the average occupancy levels, especially according to income levels. Thus, the greatest drops in employment occurred in the richest neighbourhoods, especially in central areas. In the periphery, the drop in occupancy is greater in high-income neighbourhoods (green), while the lower-income neighbourhoods, both in the centre and in the periphery, maintained the highest average occupancy throughout the period (Fig. 10, bottom).

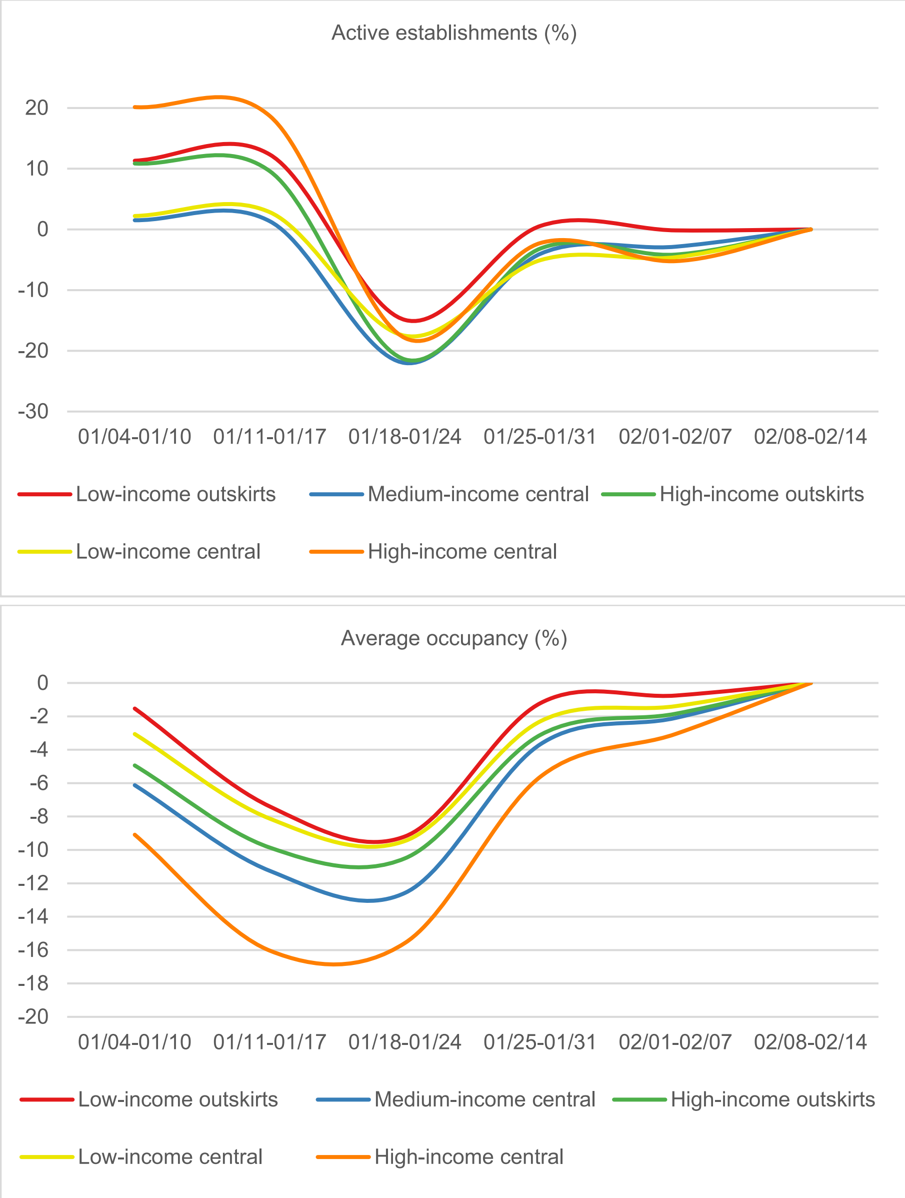
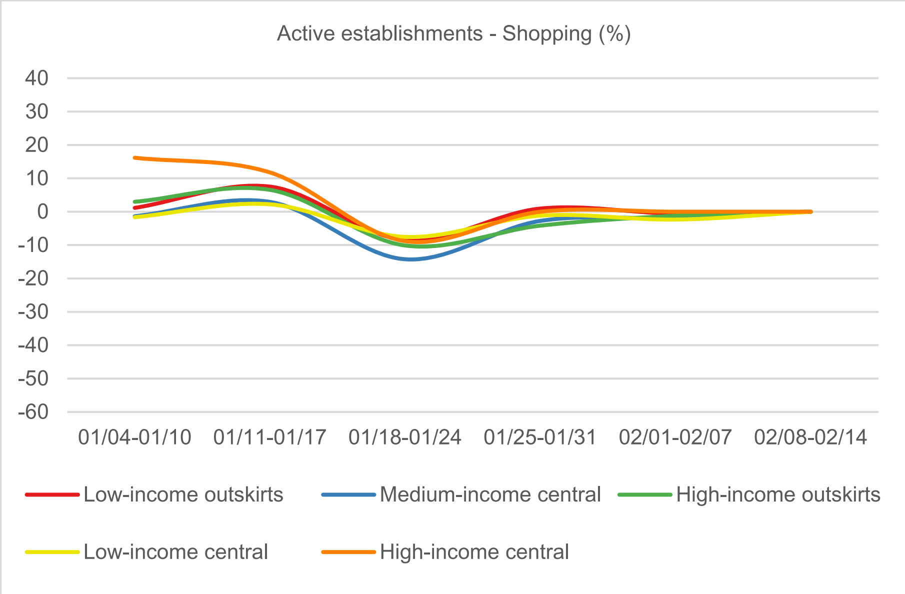


Fig. 10. Changes in total active POI and average occupancy with respect to the reference week and by type of neighbourhood. Source: Own elaboration from Google Places – Google Popular Times.

According to activity categories, the differences by neighbourhood types in the behaviour of POIs linked to Shopping were very small, especially in the total number of active POIs. In average occupancy, the drop was once again greater in the wealthier neighbourhoods in the city centre. However, when it comes to dining, there were important differences between the richest areas, especially between the most peripheral neighbourhoods. In fact, the greatest differences occurred in the behaviour of the dining POIs between the areas with the highest and lowest income, both on the outskirts and in the city centre (Figs, 11 and 12).

Tables 6 and 7 shows the drop and recovery rates in the week of the snowfall for each of the clusters, occupation and active establishments, respectively. The drop rate have been calculated taking into account the week with the greatest decline, which for occupancy (Table 6) is the second week of January, and for active establishments, it is the third week of January (Table 7), in both cases, taking into account the previous week. The recovery rate has been calculated from the week with the lowest point reached, in both cases, the third week of January, and the percentage increase is calculated with respect to the following week. The central High-income cluster is observably the one with the greatest drop and, in turn, the greatest rate of recovery. Regarding categories, as has been seen throughout the analysis, the Dining category was the most affected, but with less incidence in the poorest neighbourhoods (cluster Low-rent outskirts and Low-rent central).



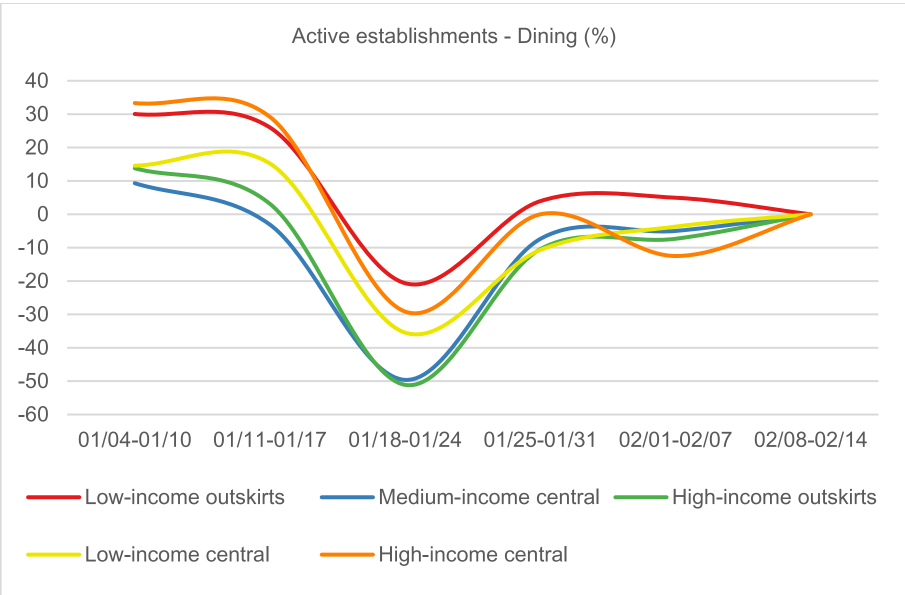


Fig. 11. Changes in the number of active POIs in shopping and dining with respect to the reference week and by type of neighbourhood. Source: Own elaboration from Google Places – Google Popular Times.

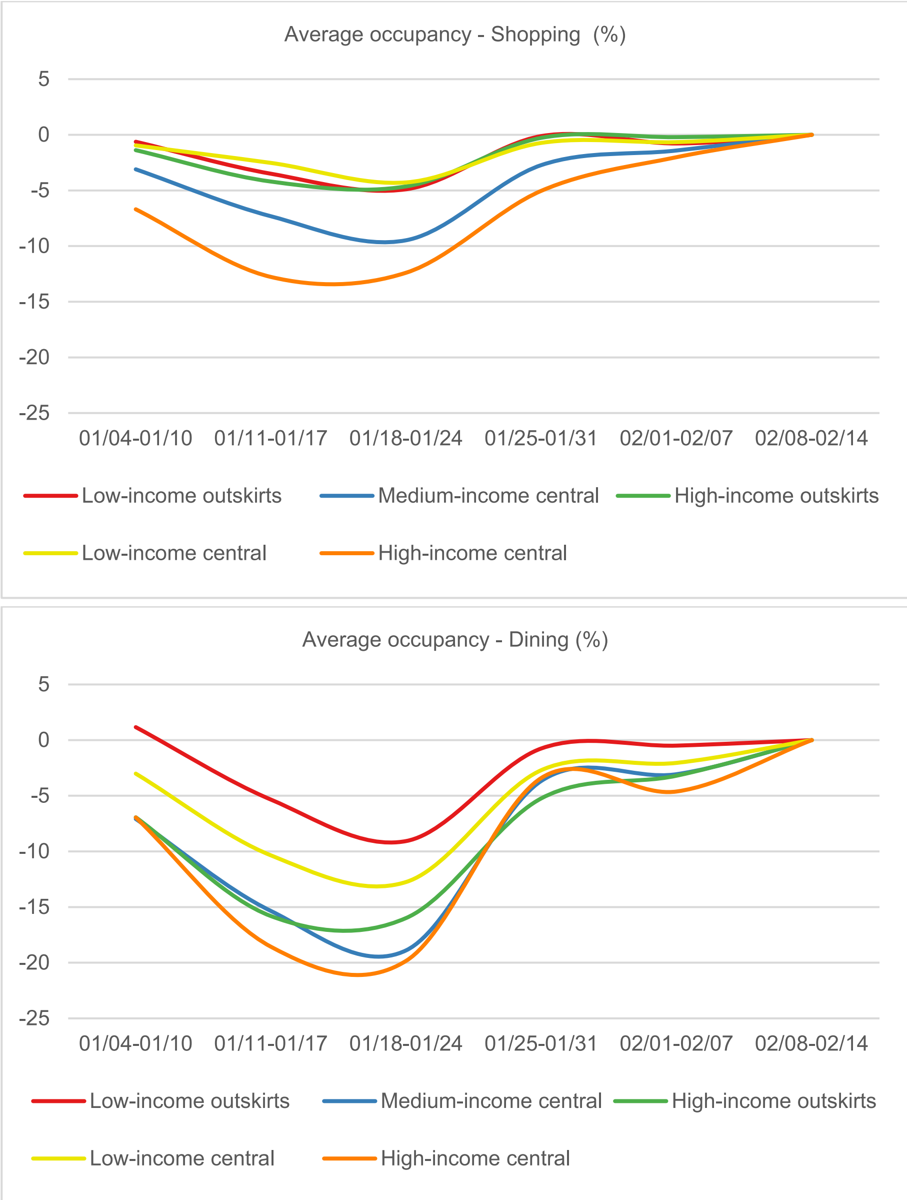


Fig. 12. Changes in the average occupancy of active POIs in shopping and dining with respect to the reference week and by type of neighbourhood. Source: Own elaboration from Google Places – Google Popular Times.

Table 6
Occupancy - drop rate and recovery rate per cluster. Source: Own elaboration from Google Places – Google Popular Times.

CLUSTER	Drop rate (%)			Average occupancy	Recovery rate (%)			Average occupancy
	Total	Dining	Shopping	Second week January	Total	Dining	Shopping	Reference Week
Medium-income central	−5.14	−8.27	−4.22	17.53	8.90	15.23	6.76	28.27
High-income central	−6.95	−11.62	−6.08	17.27	9.95	16.43	7.36	31.29
Low-income central	−5.07	−7.35	−1.57	16.31	7.16	10.05	3.55	23.19
Low-income outskirts	−5.87	−6.51	−2.88	17.23	7.98	8.32	4.78	28.27
High-income outskirts	−4.92	−8.88	−2.82	18.10	7.39	10.75	4.37	28.50

Table 7
Active establishment - drop rate and recovery rate per cluster. Source: Own elaboration from Google Places – Google Popular Times.

CLUSTER	Drop rate (%)			POIs Onlive	Recovery rate (%)			POIs Onlive
	Total	Dining	Shopping	Third week January	Total	Dining	Shopping	Reference Week
Medium-income central	−23.51	−58.93	−12.90	739	17.99	42.26	11.50	952
High-income central	−38.06	−62.5	−25.00	209	15.67	29.17	8.82	275
Low-income central	−19.73	−50.04	−5.9	722	12.47	24.79	6.38	876
Low-income outskirts	26.23	−50.71	−9.62	809	15.49	24.61	9.42	955
High-income outskirts	−32.28	−64.89	−13.10	275	18.29	40.67	5.95	355

5. Discussion

The analysis of Google Popular Times (GPT) has provided a rich variety of results, a direct consequence of using a database of over 4000 locations in seven different weeks. However, working with data from Google Places and the activity of POIs in GPT involves challenges and has limitations that should be considered (Martí et al., 2019).

One initial challenge lies in the dependency on data availability and accessibility. This type of data is subject to changes in privacy policies and settings, which affect users and companies, and may limit data access or usefulness. Specific techniques are required for data access and may change in the future. In addition, the data provided determines the type of analysis. In our case, the POI occupancy values are relative, while total occupancy data would have allowed a much more realistic analysis of changes in densities.

Once the data are obtained, it is necessary to harmonize the dataset prior to visualization or analysis, to avoid errors, over-presence, or duplicate information (Martí et al., 2019). In Google Places the POIs are registered by the users, and sometimes POIs are registered twice with a different name. Previous experience has shown that a Google Places dataset could include up to 2% duplicate listings. Other problems have to do with the assignment of POIs to categories. Some categories are too general, and/or some places may not have assigned a specific sub-category, thus it is not clear what type of place they represent. Finally, the data is not exempt from bias, especially in POIs with live-streaming in GPT. Larger or certain categories may be overrepresented, while smaller POIs or certain categories may be underrepresented. This can unequal effects on different city areas, for example, with more presence of POIs with live-streaming in GPT in the centre and less in the periphery. In Madrid this bias is not important, because there is a very high proportion of POIs with live-streaming data (almost 30% of the total), but this limitation of GPT can affect studies in cities where the proportion of live-streaming is lower.

One way to overcome these potential limitations when evaluating the impact of extreme weather events on urban dynamics is by utilizing various sources in a complementary manner. These sources can include social networks like Twitter, data from urban sensors such as traffic loop detector, pedestrian counter data (Talavera-Garcia and Pérez-Campaña, 2021), or mobile phone data.

In any case, our analyses provide evidence of great interest. The considerably different drop in activity according to the types of activities was outstanding. Those activities that were most relevant to the population, such as public facilities and shopping, came up as less vulnerable and more resilient (lower drop and faster rate of recovery). In contrast, optional and non-essential activities, such as entertainment or dining, were those that experienced the sharpest drop and a slower recovery rate. The distinction between necessary and optional activities has been considered in previous urban studies aiming at explaining human behaviour and preferences (Jose Carpio-Pinedo, 2020; Gehl, 1987). Our results may prove that people postpone non-essential activities during extreme weather disturbance, like the great snowfall of Storm Filomena.

Further, due to their greater spatial detail, the results make it possible to relate the impact of the heavy snowfall with very unequal distribution factors in the same city. For example, we have been able to see that the lowest-income neighbourhoods, both in the centre and on the periphery, showed the greatest resilience throughout the period, measured through the average occupancy of their points of interest. The unequal distribution of social groups in the city, based on their socio-economic level, ethnicity or other difference factors, is known as socio-spatial segregation (Logan and Molotch, 1987) and is directly linked to the unequal access of certain groups to services and opportunities, but also to a very different exposure to environmental risks such as air or water pollution, with a direct impact on health (Ard, 2016; Woo et al., 2019). Likewise, we were able to anticipate that the high socio-spatial segregation in Madrid (Musterd et al., 2017) and the unequal distribution of urban activity (José Carpio-Pinedo and Gutiérrez, 2020) would entail an unequal impact of the great Filomena snowfall.

However, the results are counterintuitive, since the impact was greater in neighbourhoods with a higher socio-economic level, the POIs of the poorest neighbourhoods maintaining better average occupancy levels. The study primarily focuses on characterizing the observed differences rather than exploring their underlying explanations, which remain beyond the designated scope. The causes of these results cannot be deduced from the data. However, several hypotheses could be proposed:

- Firstly, the usual greater presence and density of trees in higher-income neighbourhoods (Foster et al., 2022; Grove et al., 2006). After the snowfall, multiple trees and branches collapsed, hindering mobility in the streets and public spaces (Pérez González et al., 2022).
- A second hypothesis would be the greater independence of high-income households, whose inhabitants, in adverse situations, have ample resources to request services at home while remaining sheltered. In contrast, the humblest households have fewer resources and facilities at home, it being necessary to travel to different establishments, despite the adverse conditions and the extra effort required.

- A combination of the above two.

We should observe that, from objective data like the number of establishments open and the number of people in them, the discussion of vulnerability and resilience could become more complex, especially if it implies an evaluation of the degree of need of a certain activity in light of socio-economic inequality and in diverse urban contexts.

A continuation of this work could set the objective of constructing an explanatory model, based on several factors that describe the characteristics of both the built environment, its population and the services available, all at a detailed spatial scale (intraurban).

6. Conclusions, further research and applicability

"We are confronted by an interesting challenge. As a technically advanced urban society, we have at our disposal the organizational and inventive abilities to deal successfully with snow, a menace that often severely hampers activity in our major centers. Why do we not use them?" (Rooney, 1967; p. 559).

The time to use technology to face extreme climate events is now. Newly available, real-time, big data sources in combination with advanced analysis tools can serve as the base for our societies to evaluate the disruption and resilience of urban environments facing extreme weather conditions and take actions to adapt and reduce vulnerability to these risks (McBean, 2004).

The main novelty of this paper is having used geolocated data from social media platforms and spatial analysis tools to examine the effects of an extreme weather event on diverse activities at the intra-urban scale. Our results have shown the potential of these newly available data –in particular from Google Places POI and GPT– for providing a comprehensive understanding of how a heavy snow event impacted on urban functions, describing the disruption and resilience of activities, as disaggregated by category. The high spatial and temporal resolution of these geolocated data and spatial analysis techniques within GIS allow effective monitoring of the distribution of impacts within the city, and to assess the effects on different socioeconomic types of neighbourhoods.

Indeed, the decrease in activity in the city of Madrid during the weeks affected by the significant snowfall event in 2021 (Filomena) was assessed. The results reveal a decline in occupancy from the onset of the snowfall, but the impact on the closure of establishments was delayed. The snowfall resulted in significantly low occupancy levels, which explain the later temporary closure of numerous activities. The results also demonstrate the prolonged effects of the snowfall, which persisted for almost three subsequent weeks. Just three weeks after the snowfall, there was a slight recovery in occupancy rates, although the total number of open points of interest (POIs) remained significantly lower than under normal circumstances.

The results also have shown that the questions of vulnerability and resilience of urban activities facing climate change are complex and related to its degree of need, socio-economic factors, and the built environment. Thus, the impact was also very different depending on the type of activity and types of neighbourhoods. Essential day-to-day activities experience less impact compared to leisure-oriented activities. On the other hand, neighbourhoods with lower income showed more resiliency than wealthier neighbourhoods.

The data and methods used in this research can be replicated under other types of extreme disruptions, and have important implications on societal issues, livelihood and policy-making process. The ability to spatially and temporally analyse the impact of events on activities is one of the management functions of smart cities. First of all, spatial analysis makes it possible to identify the most affected areas, determining the places where intervention is required, such as street cleaning. The real-time monitoring of the impact has a direct applicability for disaster management and rapid decision-making, with great benefits under situations of such emergency. Moreover, analysing the impact of natural disasters in more precise spatial detail is fundamental for informing effective policies to reduce vulnerability and increase resilience, by anticipating and mitigating the effect of these events with fine contextual awareness. Prevention is financially worth it. A single storm can cost a city considerably more than what it is necessary to prevent and set up organization and snow-control programs. A higher preparedness results in a lesser disruption and lower economic costs (Perry and Symons, 1980).

Further research could take these results one step further to analyse the causes of the uneven levels of vulnerability and resilience, for instance, using multivariable regression models or developing simulation models. This approach would help isolate and compare the key factors on which policies should focus. In addition, it would be highly pertinent to incorporate the economic dimension and undertake comparisons of occupancy levels with methodologies that assess the economic losses incurred as a consequence of such events. To achieve that task, it would be necessary to analyse newly available data sources at the suitable spatial and temporal disaggregation level, such as credit card consumption big data (Carpio-Pinedo et al., 2022).

CRediT authorship contribution statement

Enrique Santiago-Iglesias: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft. **José Carpio-Pinedo:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Wenzhe Sun:** Software, Investigation, Writing – review & editing. **Juan Carlos García-Palomares:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Visualization, Supervision.

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.

Data availability

Data will be made available on request.

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