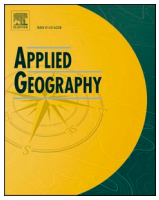
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The city turned off: Urban dynamics during the COVID-19 pandemic based on mobile phone data

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ABSTRACT

Due to the rapid expansion of the COVID-19 pandemic, many countries ordained lockdowns, establishing different restrictions on people's mobility. Exploring to what extent these measures have been effective is critical in order to better respond to similar future scenarios. This article uses anonymous mobile phone data to study the impact of the Spanish lockdown on the daily dynamics of the Madrid metropolitan area (Spain). The analysis has been carried out for a reference week prior to the lockdown and during several weeks of the lockdown in which different restrictions were in place. During these weeks, population distribution is compared during the day and at night and presence profiles are obtained throughout the day for each type of land use. In addition, a spatial multiple regression analysis is carried out to determine the impact of the different land uses on the local population. The results in the reference week, pre-COVID-19, show how the population in activity areas increases in each time slot on a specific day and how in residential areas it decreases. However, during the lockdown, activity areas cease to attract population during the day and the residential areas therefore no longer show a decrease. Only basic essential commercial activities, or others that require the presence of workers (industrial or logistics) maintain some activity during lockdown.

1. Introduction

Different pandemics have altered the rhythm of cities, even in recent years (Hanson, 2006, p. 232). However, none have impacted modern living as much as the current COVID-19 pandemic. This pandemic has suddenly changed the way in which citizens interact, move or make use of different urban activities. The change has been radical. In particular in the early phases of the pandemic, with the adoption of the most severe measures and the lockdown, which has led to the closure of most activities and changes in habits when carrying out the most basic activities. Without any warning, cities were forced to slow down, reduce and even stop much of their activity for months. Knowing how the pandemic has transformed urban dynamics and what the patterns of these dynamics are in the phases of lockdown and subsequent restrictions is essential for decision-making, establishing new measures or evaluating their effectiveness in preventing and controlling the spread of the pandemic and in understanding the city's resilience to these measures to contain severe outbreaks.

Big Data obtained from geolocated devices provides valuable spatial and temporal information to evaluate measures implemented to prevent and control of the spread of the pandemic (Zhou et al., 2020). In particular, due to the heterogeneity and large size of the sample as well as the high temporal granularity, anonymous mobile phone records constitute an excellent source of Big Data for the analysis of the distribution of the population throughout the day. Each user's activity records allow the reconstruction of their spatio-temporal trajectories, differentiating between the time they remain in one place and that taken to move between places (trips). This information is crucial for the analysis and modelling of the spread of the disease.

The possibilities offered by new geolocation technologies to study population mobility and the possible spread of contagious diseases are well known (Sirkeci & Yucesahin, 2020; Ferretti et al., 2020). Mobile phone data had only been rarely used in epidemiological research, but their enormous potential has been demonstrated during the COVID-19

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pandemic. Despite the short time that has elapsed since the beginning of the pandemic and the restricted access to these data, researchers and governments have started to collaborate with private companies, particularly mobile network operators and location intelligence companies, to estimate the effectiveness of the control measures in a number of countries, including Austria, Belgium, Chile, China, Germany, France, Italy, Spain, United Kingdom, and the United States (Oliver et al., 2020a).

Oliver et al. (2020b) have reviewed how mobile phone data can help to tackle the COVID-19 pandemic. In their work, they classify the investigations that have used mobile data according to the type of questions they are trying to answer or according to the actual time at which they appear during the pandemic. In general, studies using mobile phone data have focused, on the one hand, on the analysis of the population's mobility patterns during the different phases of the pandemic. These studies evaluate the follow-up and impact of the lockdown in different countries according to the number of people who stopped traveling during this period and, therefore, remain at home (see Badr et al., 2020; Gao et al., 2020; Lai et al., 2020; Kraemer et al., 2020; Pepe et al., 2020; Pullano et al., 2020). In some cases, sociodemographic differences have been further examined in the monitoring of the measures (Bushman et al., 2020) or in the analysis of the temporal changes in human mobility behavior, social contact rates, and their correlations with the transmissibility of COVID-19 (Paez et al., 2020; Yabe et al., 2020). On the other hand, another group of works has used mobile phone data to analyze the spread patterns of COVID-19 and build predictive models on the expansion of the pandemic. Mazzoli et al. (2020) or Sun et al. (2020, p. 13860) have used the mobility data obtained from mobile telephones to analyze and model how the epidemic has spread in Spain and the United States, while Peixoto et al. (2020) use mobility data to model future scenarios in the possible expansion of the pandemic in Brazil or Aleta et al. (2020) to model possible second-wave scenarios once restrictions have been lifted.

The objective of this paper is to study the impact of the pandemic on the dynamics of the city throughout the day and its spatial relationship with land uses, an aspect that the authors believe has not as yet been discussed in depth. The presence of the population in each area of the metropolitan area of Madrid (Spain) is calculated throughout the day using information from mobile phones. This daily distribution of the population is analyzed for a typical week, taking as reference the period between February 14 and 20, 2020, and is compared with the daily distributions in the weeks of confinement decreed due to the state of emergency in Spain. During this lockdown period, we also analyze the effects of the different phases, where measures to restrict the mobility of the population and the opening of the different activities have been tightened or eased.

In order to analyze urban dynamics, mobile phone data were crossed with the distribution of land uses within each transport zone. Typical hourly activity profiles have been obtained for each land use and multiple regression models (OLS and spatial models) have been calculated for four major moments in time (morning, afternoon, evening and night). The methodology implemented is similar to that used in García-Palomares et al. (2018), where urban dynamics were analyzed through Twitter activity in each area of Madrid. However, in our case, it is applied to the lockdown and containment scenarios in response to the COVID-19 pandemic. Furthermore, spatial regressions have been used to improve the quality of the models and mitigate the problems of spatial autocorrelation in the distribution of the residuals. The analyses carried out show the level of activity throughout the day that each type of land use has maintained according to the degree of restrictions imposed.

This paper contributes to the literature in several ways. First, unlike most previous studies, a highly detailed spatial scale is used. This article does not focus on the impact of the measures in the study area as a whole, but rather analyzes the distribution of their impact according to the type of land use within each zone of the study area. Second, this article uses high temporal detail. Normally previous works analyze the impacts of lockdown on total daily mobility. Here we have analyzed how the type of measures imposed are reflected in the changes in the hourly distribution of the population present in each zone, week by week. Third, in this article data on the hourly distribution of the population are crossed with the distribution of land uses, to analyze the impact of the measures on the temporal dynamics of the different urban activities. Only Google's COVID-19 Community Mobility Report[1] performs a similar analysis, but with aggregations in large territorial units (regions and countries). However, here we have gone further. Mobile phone data have been used to reconstruct the trips between transport zones (whose area is usually of a few m^2) and crossed with the information on the distribution of land uses of the Cadastre within these transport zones. The crossing of information between mobile phone and land use data has allowed us to carry out regression analyses to take advantage of the high level of detail of the land use data, in addition to temporal distribution profiles for each use. Profiles have been constructed based on the dominant land use in each area, since mobile phone data do not have sufficient spatial resolution to determine the land use by each resident present at any given time of the day. We know the size of the population present in each transport zone in each time zone, but not their exact location (land use) within each transport zone, since most of these zones are used for different purposes. However, the regression analysis allows us to obtain an accurate calculation of the weight of each form of land use by the population present in the transport zone and during each week of the lockdown.

The selection of the Madrid metropolitan area as a case study is also of special interest, given the high impact that the disease has had. Spain has been one of the countries most affected by the pandemic, with rates of confirmed cases and deaths among the highest in the world: more than 270,000 total cases at the end of July 2020 (Johns Hopkins University, 2020), which means almost 6000 cases per million inhabitants. Madrid has been the most affected metropolitan area. In addition, it was one of the first affected areas in Europe to establish a lockdown and has also witnessed various phases in the application of the measures. These measures were strictly respected by citizens during the weeks of study, partially due to a remarkable level of police surveillance across the city. Because of this, the study allows us to evaluate the impact of different types of measures and serves as a reference in the evaluation of the same.

Although this paper does not study the relationship between the mobility restrictions and the control of the pandemic spread, it is important to highlight the overall effectiveness of the severe lockdown measures to contain the unexpected explosive situation of the first wave. The Madrid Region reached a peak of almost 3500 new COVID-19 cases per day during the last week of March, while the reported new cases in mid May were around 300 per day (Consejería de Sanidad de la).

The remainder of this paper is structured as follows. Section 2 describes the study case, including the data and the methodology used. Section 3 describes results, and Section 4 contains the conclusions.

2. Case study, data and methodology

2.1. Study area and phases

The selected study area covers the municipalities of the Morphological Urban Area (MUA) (ESPON, 2014) of Madrid that are located within the Region of Madrid. With an extension of 202,478.46 Ha, the study area enables us to analyze Madrid's behavior on a metropolitan scale, and study in detail what happens in each of the 1062 transport zones into which it is divided (Figs. 1 and 2). Just over 5.7 million people reside in the metropolitan area of Madrid according to the 2019 census, and its population increases to almost 5.9 million people in the morning hours due to the balance of people commuting to and from outside the metropolitan area.

[1] https://www.google.com/covid19/mobility/(accessed 07.09.20).

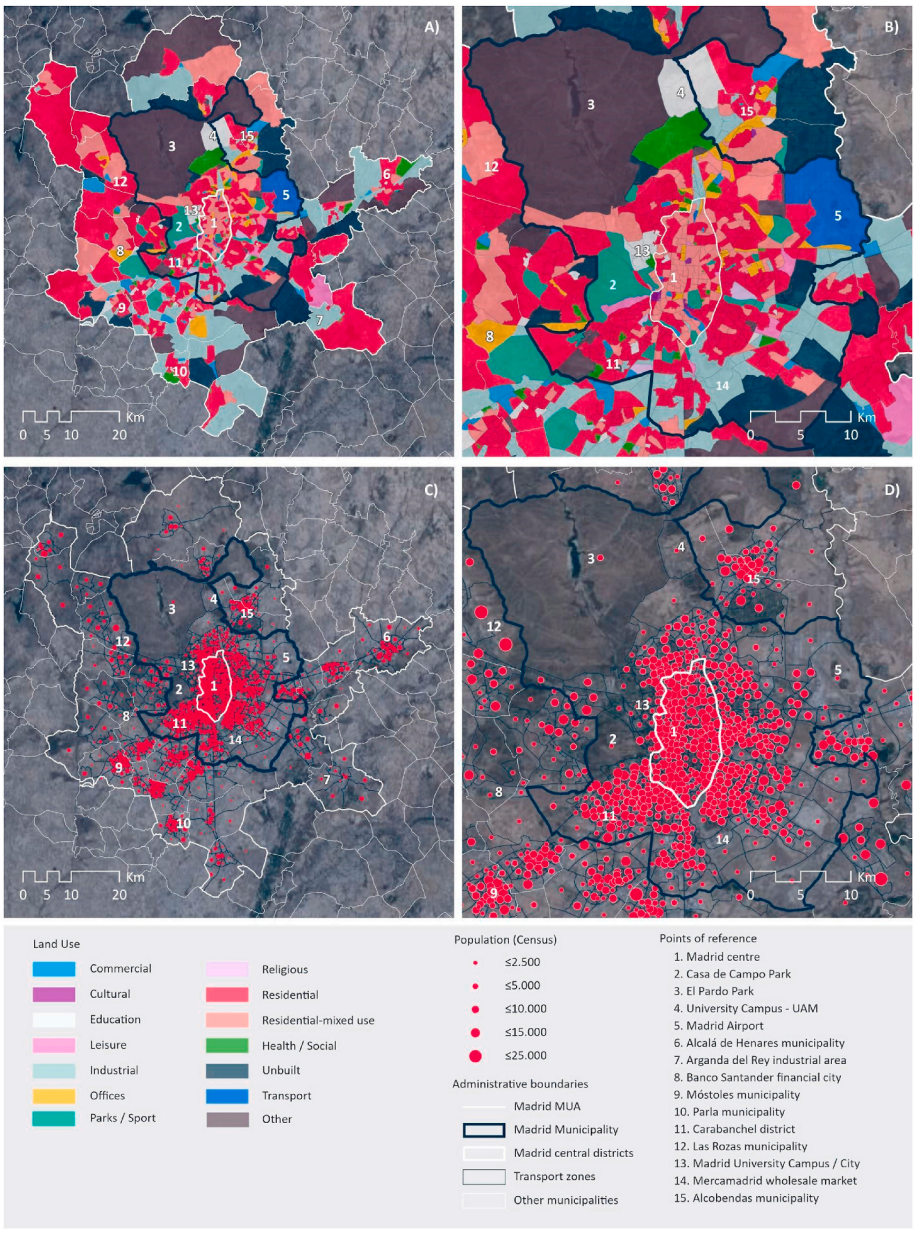


Fig. 1. Land Use and Distribution of population (in the reference week at night) in the study area.

Regarding the time frame, the research analyzes the impact of the COVID-19 pandemic on the distribution of the population in the study area over 6 weeks (March 23 - May 10, except Easter). In these weeks, the Government of Spain had activated the State of Alarm prior to the adoption of the Transition Plan to the New Normal. They were the weeks of greatest restrictions, with various measures to regulate activities in the different phases. Additionally, the analysis extends to the week of February 14–20, 2020, taken as a reference (W0), representing the distribution of the population in a normal week, prior to the pandemic. The weekly analysis allows us to study the impact of the different measures decreed by the government on mobility and the degree of confinement of the population.

To understand the results obtained, the phases of the lockdown decreed by the Government of Spain and the most important measures established in each of them (Table 1) must be defined. Table 2 shows the dates of the study weeks, relating them to the phases and measures indicated in Table 1.

The results for the reference week (W0) are shown in all analyses. For reasons of space, sometimes only the results for weeks W1, W2, W4 and W6 are shown, which are a good reflection of behavior in the different phases of the State of Alarm. In other cases, the comparison is made between the reference week (W0) and the week with the greatest restrictions (W2).

2.2. Data sources and data preprocessing

2.2.1. Data sources

The data sets on which this study is based are described below:

1. **Mobile phone records.** The data used for the extraction of mobility indicators consists of a set of anonymized mobile phone records corresponding to the defined weeks of study, obtained through a collaboration agreement with one of the three main Mobile Network Operators (MNOs) in Spain, with a market share of more than 20 %. The homogeneous penetration of the MNO in virtually all socioeconomic groups of the population, together with the size of the sample, grants a good representativeness of the whole Spanish population. The records include Call Detail Records (CDRs), produced every time

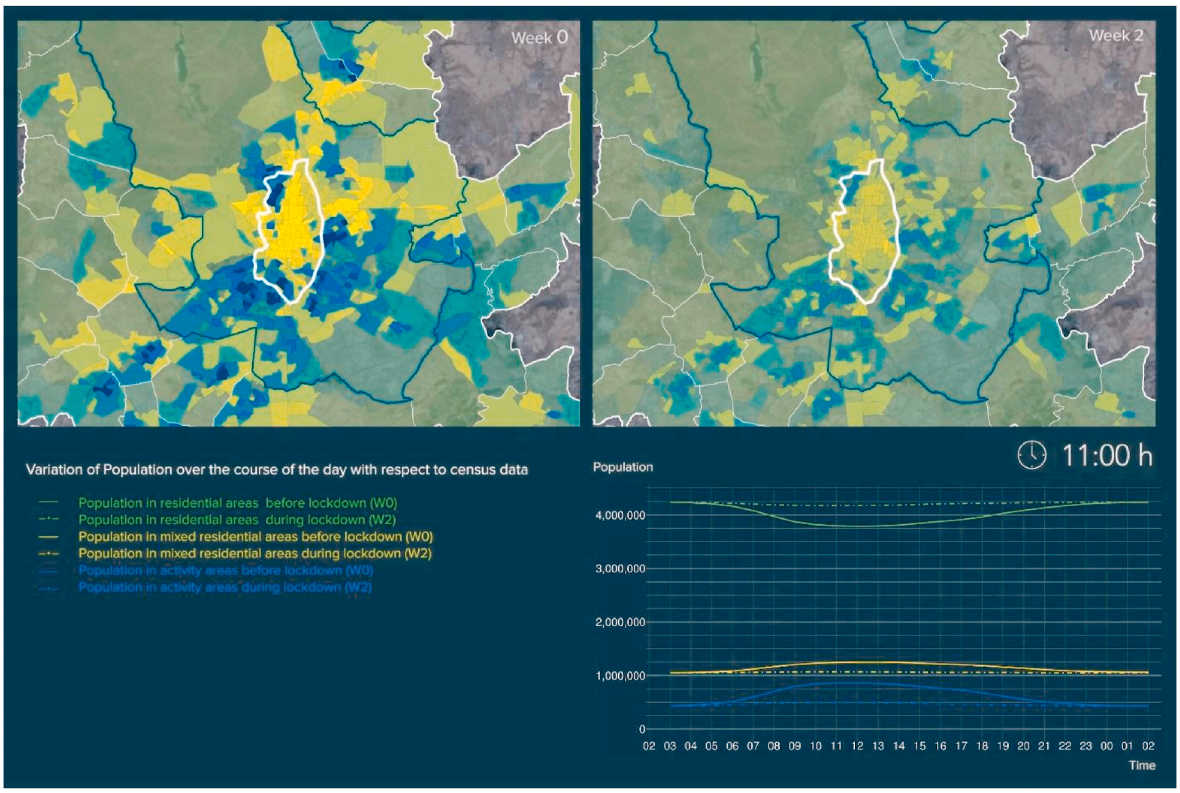


Fig. 2. Layout of the video-visualization representing the variation of population density according to time slot for the reference week (W0) and the second week of the lockdown (W2).

a mobile phone interacts with the network through a voice call, a text message or an Internet data connection, as well as passive events coming from network probes. Among other information, each record contains an anonymized identifier of the user, a timestamp and the position of the tower to which the device is connected at that particular moment. This provides an indication of the geographical position of the user at certain moments along the day. The registers do not provide the exact location of the users. This typically provides an accuracy of dozens or hundreds of meters in urban environments, and up to a few kilometres in rural areas, where the mobile network is less dense. The temporal resolution of the records depends on the frequency of use of the mobile device; most users typically generate a register at least every 15–20 min.

2. **Land Use data.** Land use data provided by the Directorate General for Cadastre in Spain (Cadastre), by built entity of the study area. The databases define the surface area [m^2] of each type of land use. These data are updated every 6 months and the data set used corresponds to the update of January 24, 2020. Fig. 1 represents the transport zones of the study area according to this classification of predominant land uses (see section 2.4).
3. **Population Data.** Census data for 2019 at the census section level, obtained from the National Institute of Statistics. The data has been aggregated at the transport zone level, and it has been used as the sampling frame for expanding the sample of the MNO customers. Fig. 1 shows the population distribution in the study area according to the Register.
4. **Territorial boundaries.** The demarcation of the Morphological Urban Area (MUA) of Madrid has been obtained from the ESPON DATABASE project. Only the municipalities belonging to the Region of Madrid have been considered for this study. The transport zones defined in Madrid have been obtained from the Open Data Portal of the Consorcio de Transportes de la Comunidad de Madrid.[2]
5. **Data on State of Alarm phases and measures.** They come from the Royal Decree of the Ministry of the Presidency of the Government of Spain published in the Official State Gazette.

2.2.2. *Phone data preparation*

The extraction of activity and mobility information from mobile phone records consists of the main following sub-processes:

1. **Data pre-processing and cleansing**: mobile phone registers are pre-processed to ease their storage and management. An integrity analysis is also performed to filter out errors in the raw data, in order to ensure the quality of the results. It is important to detect and fix these errors to avoid the incorrect detection of trips.
2. **Sample selection**: an effective sample is built by selecting only those users with enough mobile phone activity such that it is possible to reconstruct their mobility and activity patterns with an adequate level of accuracy and reliability. In addition, the data have been processed to discriminate the trips made on a recurring basis by potential transport professionals, i.e. those who make more than 6 trips a day and travel over 50 km, than those made by travellers.
3. **Extraction of activity-travel diaries:** an "activity" is defined as an interaction or set of interactions with the environment that takes place in the same location and motivates an individual to move there. A "trip" is defined as a sequence of one or more displacements ("stages" or "legs") between two consecutive activities. This way, a trip has a main purpose determined by the activity at origin and/or the destination. Different criteria based on stay times, itineraries and longitudinal behavioural patterns are used to identify activities,

[2] https://data-crtm.opendata.arcgis.com. (accessed 05.06.20).

Table 1
Phases, dates and measures adopted by the Spanish Government during the lockdown.

Phase	Dates (2020)	Summary of measures
Declaration of a State of Alarm	14–28 March	● Suspension of face-to-face classes in all learning centers. ● Prohibition to circulate in the streets, except for: Buying food or medicine, going to health centers, going to or coming from the workplace, going to banks or insurance companies, taking care of the elderly or children. ● Recommendation of teleworking (most companies where it was possible adopted this recommendation) ● Closure of most premises, shops and businesses. Exceptions: Food stores, pharmacies, medical centers, gas stations, and others. ● Closure of museums, libraries and leisure or sports centers. ● The public transport service is maintained, with exceptional measures depending on the specific service.
Extension of State of Alarm 1	29 March - 12 April	This is the phase with the greatest restriction of activities. The measures adopted during the State of Alarm also include: ● Suspension of non-essential face-to-face work activity. Fundamentally, the following are considered essential activities: health, food and fuel distribution, public maintenance services, cleaning and waste collection, state security, postal services, funeral services and the media.
Extension of State of Alarm 2	13–26 April	Measures relating to those defined in the previous phase: ● People are allowed to return to their workplaces for non-essential activities where teleworking measures cannot be implemented. ● Circulation of private vehicles is allowed to carry out the permitted activities.
Extension of State of Alarm 3	27 April - 10 May	Measures relating to those defined in the previous phase: ● Children under 14 years of age may go out with someone 1 h a day but must not go further than 1 km from home. ● From 2 May: Those defined by the Transition Plan to the New Normal.
Transition Plan to the New Normality: De-escalation - Phase 0	2–10 May	On April 28, a 4-phase Transition Plan to the New Normal was established. On May 2, Madrid enters Phase 0 of the plan, allowing: ● Departure for minors, individual non-contact sports activities and walks, once a day and at regulated hours. ● Opening of establishments by appointment for individual customer service.

trips, intermediate stops subordinate to the trip and the different stages or legs of a trip. The result of this process is the sequence of activities and trips performed by each user in the sample for the period of study. The information associated to each activity includes its location, the start and end times, and the type of activity: home, work, study, other frequent activities, non-frequent activities (e.g., based on the analysis of the user's longitudinal behavioural patterns during several weeks/months, the place of residence of each user is identified as the place where the user sleeps more often). Once activity diaries are extracted at an antenna level, a layer of land use information is used to refine the estimation of the user position inside antenna coverage areas. Users are assigned to different areas served by the same antenna through a probabilistic method that takes into account the type of land use (residential, commercial, industrial, etc.). The information associated to each trip includes its origin and destination (i.e., the locations of the preceding and subsequent activities), the start and end times (i.e., the end time of the preceding activity and the start time of the subsequent activity), and the location and the start/end times of the intermediate stops (if any).

4. **Expansion of the sample to the total population**: in order to extract meaningful mobility indicators, the sample is expanded to the total population of Spain. This expansion is performed at transport zone level. The expansion factor is calculated as the ratio between the number of residents of the district according to the census information and the sample of users with their home location at the given district. This procedure allows the correction of any possible spatial heterogeneity of the MNO's market share.
5. **OD matrices generation**: In the present study the expanded activity travel diaries extracted from mobile phone records were used to build OD matrices with origin and/or destination in the Region of Madrid. The matrices were segmented by day and start time of the trip, considering 24-time segments. The zoning used for trips aggregation consisted of the 1259 transport zones defined for the Community of Madrid, in addition to 51 external zones that refer to the rest of the provinces of Spain. These data have enabled us to calculate the presence of the population each hour of the day in the 1062 zones of the study area.

Table 2
Study weeks, dates and correspondence with the State of Alarm phases.

Study weeks	Dates	Corresponding phase
W0	14–20 February	Reference week. Normal activity prior to COVID-19, before the state of alarm
W1	23–29 March	Second week after the Declaration of the State of Alarm
W2	30 March - 5 April	First week of Extension of State of Alarm 1
W3	13–19 April	First week of Extension of State of Alarm 2
W4	20–26 April	Second week of Extension of State of Alarm 2
W5	27 April - 3 May	First week of Extension of State of Alarm 3
W6	4–10 May	Second week of Extension of State of Alarm 3 and First week of Transition Plan to the New Normality: Phase 0

2.3. Analysis of the spatial distribution of population according to time slot

Population distribution in the study area varies throughout the day as a consequence of the different activities carried out. For analysis purposes, the number of people present in each transport zone for each hour and week was estimated from the *O*-D matrices. The following criteria were considered:

1. A single matrix of hourly trips per week was obtained, in which the average number of trips for each *O*-D pair is the average of the trips made between Monday and Thursday of that week.
2. It was considered that the number of people in the census corresponds to the number of people present in each transport zone at 02:00, when the lowest number of trips generated in W0 in the study area is observed.
3. The number of people present in each transport zone per hour was estimated as those indicated in the census (situation 02:00 h) plus the sum of average weekly trips of people attracted to that transport

zone, between 02:00 and the corresponding time, minus the sum of average trips for the week generated in that transport zone for the same time period. If negative populations are obtained, they become zero. The process takes into account the entire day.

An initial exploration of the data was carried out through video-visualization, which represents the evolution of the population density [people/km^2] for each time slot in the reference week (W0) and the week of greatest restrictions (W2) (see video available in the supplementary material). The two weeks are shown simultaneously and according to the same symbology, so that a visual comparison can be made. The video also contains an animated graph showing the weekly evolution of the population in each type of urban area according to the basic classification of predominant land use.

Secondly, bivariate Ordinary Least Squares (OLS) analyses were performed in order to compare the different population distributions according to time slots for each of the study weeks: Morning (08:00 to 14:00), Afternoon (14:00 to 19:00), Evening (19:00 to 22:00) and Night (22:00 to 00:00). The coefficient of determination indicates the degree of overlap between population distributions, while the regression residual maps show where differences (positive or negative) between time slot distributions emerge. This analysis was focused on differences between the reference time slot (night) and the rest of the time slots for each of the study weeks. These differences are expected to be especially high in the reference week W0 (people move within the city without restrictions) and particularly low during the week of strictest home confinement W2 (most people stay at home).

The methodology is based on comparing the presence of people in the different weeks of analysis, according to time slots, for the average of the trips made between Monday and Thursday of that week. The different weeks with mobility restrictions are compared to the week of reference and then, also among themselves, allowing us to evaluate not only the impact of the measures in relation to the normal mobility of the city, but also to the mobility which results from the application of the different measures. The methodology guarantees the comparability of the different weeks and time slots, taking into account that we estimate the presence of people following the same methodology and based on the same dataset.

2.4. Temporal profiles according to predominant land use

Temporal profiles of population presence according to predominant land use were calculated for each time slot and study week. The total number of people present in a zone was assigned to the predominant land use in the zone, and then the total number of people according to land use was added up for each time slot in order to obtain the specific temporal profile of each land use in each study week.

In order to perform this temporal analysis, the percentage of built-up area pertaining to each land use in each transport zone was calculated based on cadastral data. Firstly, three main types of transport zones were distinguished: residential (when more than 66.6 % of built-up area in the zone is residential), activity (when more than the 66.6 % is non-residential, e.g. offices, industry, retail or education) and mixed residential (all other cases). Secondly, activity (non-residential) areas were classified in 10 types: offices, industry, retail, health, education, culture, entertainment, large transport terminals, parks and others. Fig. 1 shows the predominant land use in each of the transport zones and Table 3 the built-up area per land use category and number of zones as predominant land use.

This analysis is also based on the comparison of the presence of people in the different areas of the city characterized by their main land use, during the different weeks of study. Taking into account the high reliability and accuracy of cadastral data and considering that we estimate the presence of people following the same criteria and based on the same dataset, the methodology followed guarantees the comparability of the different scenarios analyzed.

Table 3
Summary statistics of the built-up area per land use category and number of zones as predominant land use.

Land use	Built-up area [hm^2]	Zones as predominant land use
Residential	28,872	553
Mixed residential		171
Activity	24,077	338
Total	52,859	1062
Activity	**Built-up area [hm^2]**	**Zones as predominant land use**
Retail	3100	34
Culture	1441	6
Educational	333	30
Entertainment	181	8
Industrial	4,49	107
Offices	3137	41
Park and sport	4597	29
Health care	825	31
Large transport terminals	54	4
Other	5918	48
Total activity	24,077	338

2.5. Multiple regression analyses

With the aim of exploring and quantifying the impact of the different land uses on urban dynamics during COVID-19 pandemic, we have performed Multiple regression analyses. This exploration allows us to analyze the relationship between land use and people presence, overcoming the problem of land use mix within each transport zone. The dependent variable in each model was the people's presence in every transport zone per major time slot (Morning, Afternoon, Evening and Night) and study weeks. The independent variables were the amount of build-up square hectometers of each type of land use in each of the transport zones, based on cadastral data. Distance to the city center was included in the models as a control variable in order to consider the spatial component. Non-significant variables were removed from the models (blank spaces in Tables 6–8 in section 3.2).

In the first step, we performed Ordinary Least Squares (OLS) regressions, and then we analyzed the results of the model and the effect of the spatial dependence using Lagrange Multiplier (lag and error) and Moran Index. The results of Robust Lagrange Multiplier (error) revealed that spatial error was significant at the level of 5 %, while Robust Lagrange Multiplier (lag) values were significant only in one case. Therefore, we eventually performed Spatial Error Models (SEM). We selected the spatial relationship of queen contiguity in SEM because we obtained better fits with this spatial relationship than with longer distances. Here, we present the OLS results for the reference week (W0) and SEM results for all weeks. Statistical analyses were performed using GEODA software.

The coefficients of the independent variables indicate the number of additional people present as each independent variable (land use) increases by one unit. The changes in the coefficients throughout the day show the time slots in which each type of land use is most active. If the comparison is made between weeks for the same time slot, the differences in the coefficients express the extent to which the restrictions adopted in each phase of confinement affect each type of land use. The coefficients of land uses with activities that require the physical presence of workers (such as industrial) are expected to experience less variations than those used for other purposes with activities involving teleworking (for example, offices).

3. Results

3.1. Spatial distribution of population according to time slot

The visual analysis of the variation in spatial distribution of the population according to time slots in weeks W0 and W2 through video-

visualization shows a very clear picture of the impact of the measures restricting mobility and performance of activities established with the decree of the State of Alarm. During the lockdown week (W2), the population variations with respect to night-time distribution are minimal, which is also shown in the animated graph that represents the evolution of the population in each type of urban area according to the basic classification of predominant land use: residential, mixed residential and activity. However, a more detailed visual inspection reveals more significant changes in specific areas of the city, where activity registers a particularly sharp decline (for example in educational, financial or office areas) or where it remains at outstanding levels (some areas of logistics or health). Animated maps locate and identify some of these areas of interest for comparative reading of the results. Fig. 2 shows a screenshot of the video-visualization, which is attached as supplementary material in this paper.

The weekly bivariate analysis between large time slots complements the first visual approximation and allows us to obtain a numerical indicator for comparing the different scenarios. Taking night-time as the base period, the differences in distributions of the population throughout the day can be analyzed from bivariate correlations (Table 4). Madrid and its metropolitan area have a high mix of land uses, meaning that the coefficients of determination are high in all cases. The biggest differences are between night-time (residence) and morning (activities). On the contrary, between Night-time - Afternoon and, especially, between Night-time - Evening the correlations are very high, because many people have already returned to their areas of residence. The confinement situation makes the correlations between night-time and the rest of the time slots practically equal to 1. Night is reproduced during the day. However, despite how restrictive the measures have been in Madrid since the beginning of the pandemic, the different phases are reflected in the morning and night-time correlations with very high values in the most active closing week (W2) but slightly lower in subsequent weeks (W4 and W6).

The mapping of the correlation residuals between night-time and morning in weeks W0 and W2 (Fig. 3) shows a very different spatial behavior. In a normal situation (W0), the morning activity spaces become highly active (positive residual in yellow), such as office areas (Points of interest 1 and 8) and mixed areas of the center, industrial areas (Points 4, 7 or 9), large facilities, university campuses (Point 2) or hospitals, as well as transport terminals, such as railway stations or the airport (Point 3). Whereas residential areas have high negative residues (blue color).

During the week of greatest restrictions (W2) the intensity of the residuals is very low. Some equipment areas are shut off (for example, Ciudad Universitaria - Point 2) and the intensity of activity is significantly reduced in the central office spaces (Points 1 and 8). On the other hand, some industrial spaces on the periphery now show the greatest deviations (Points 4, 7 and 9), together with strategic logistics facilities, such as Mercamadrid (Point 5). Mercamadrid is the largest wholesale market in Spain, and presents an even greater deviation than in the reference week (W0), which is related to the fact that supermarkets increased sales during the first weeks of the state of alarm. Finally, attention should be drawn to the activity detected in specific points of the city, such as the Feria de Madrid-IFEMA (6), which was converted into the largest emergency hospital in Madrid during the State of Alarm.

On the contrary, residential areas tend to lose a large part of their population during the hours of activity during the reference week (W0), especially those with the highest density located to the south and northwest of the central districts of Madrid, but these losses have decreased substantially until there is practically no difference between night-time and morning in the week with the highest restrictions (W2).

Although this paper is not focused on evaluating the impact of mobility restrictions on the different socioeconomic populations groups, it is possible to draw some basic conclusions from the obtained results: We can infer that certain professionals were more affected by the restrictions than others. For instance, on the one hand, we can conclude that office workers and education professionals and staff mainly stayed at home teleworking, since, as we previously stated, the intensity of activity was significantly reduced in the central office spaces (Points 1 and 8) and education areas (2) during the week of greatest restrictions (W2). And, on the other hand, we can infer that people working in industry and logistics were the group of professionals less affected by the mobility restrictions, of course along with the health professionals, considering that industrial spaces and strategic logistics facilities show the greatest deviations (Points 4, 7 and 9), along with hospitals (6).

Table 4
Relationships in the distribution of population according to time slot (R^2).

Week	Morning 08:00 to 14:00	Afternoon 14:00 to 19:00	Evening 19:00 to 22:00	Night 22:00 to 00:00
W0 Night (22:00 to 24:00)	0.711***	0.814***	0.978***	1
W1 Night	0.987***	0.996***	0.999***	1
W2 Night	0.994***	0.998***	0.999***	1
W4 Night	0.984***	0.996***	0.999***	1
W6 Night	0.976***	0.993***	0.998***	1

***P Value < 0.001.

3.2. Temporal profiles according to predominant land use

Population distribution according to land use and time slots for the reference week (W0) is shown in Table 5 and Fig. 4a. Most of the population can be found in residential areas during all time slots. Although residential use is dominant in these transport zones, other activities, mainly commercial, services and equipment can also be found. Many of these areas therefore maintain a high population presence also during working hours (morning and afternoon). During the night time residential areas concentrate 74 % of the population. In the morning, the presence of the population in residential areas falls, but they still concentrate 65 % of the total population. This mix is even more marked in mixed residential transport zones, where the presence of the population increases during these daytime hours. But the zones that show higher fluctuation of population along the day are those classified as activity areas. These areas show a decreasing population trend from morning to night time. The population of the activity areas during the morning doubles the population of these during the night time. This population, however, represents only 14 % of the total population in the morning time and 7.5 % at night. According to the Census data a 7.2 % of the population of Madrid (more than 400,000) is resident of these areas.

Among the activities present, industrial and office areas are the ones with the largest population density. Some of the areas where industrial land is dominant also have residences, where almost 150,000 people live in these areas. These areas also receive a high number of people during working hours (morning and afternoon). During the night time industrial areas concentrate 2.5 % of the total population and office areas the 0,8 %, but in the morning time the presence of the population in these areas grows to represent 4.7 % and 2.5 %, respectively. These distributions with a higher population density in the morning and afternoon are repeated in educational, health or cultural facilities, while commercial activities or parks and sports areas have a significant population density in the evening.

Temporal profiles according to large types of land use and their behavior during the weeks of the pandemic are very different from the reference week (Figs. 4 and 5). In week W0, the departure of the population from residential areas does not compensate for arrivals, and these spaces lose more than 425,000 people during the morning hours and more than 340,000 in the afternoon. The areas of activity show an opposite profile, with very important gains in the morning (almost 410,000 people) until reaching the peak at 11 a.m. and falling during the afternoon (+310,000). The mixed areas have an intermediate situation, with positive balances both in the morning and in the afternoon, but

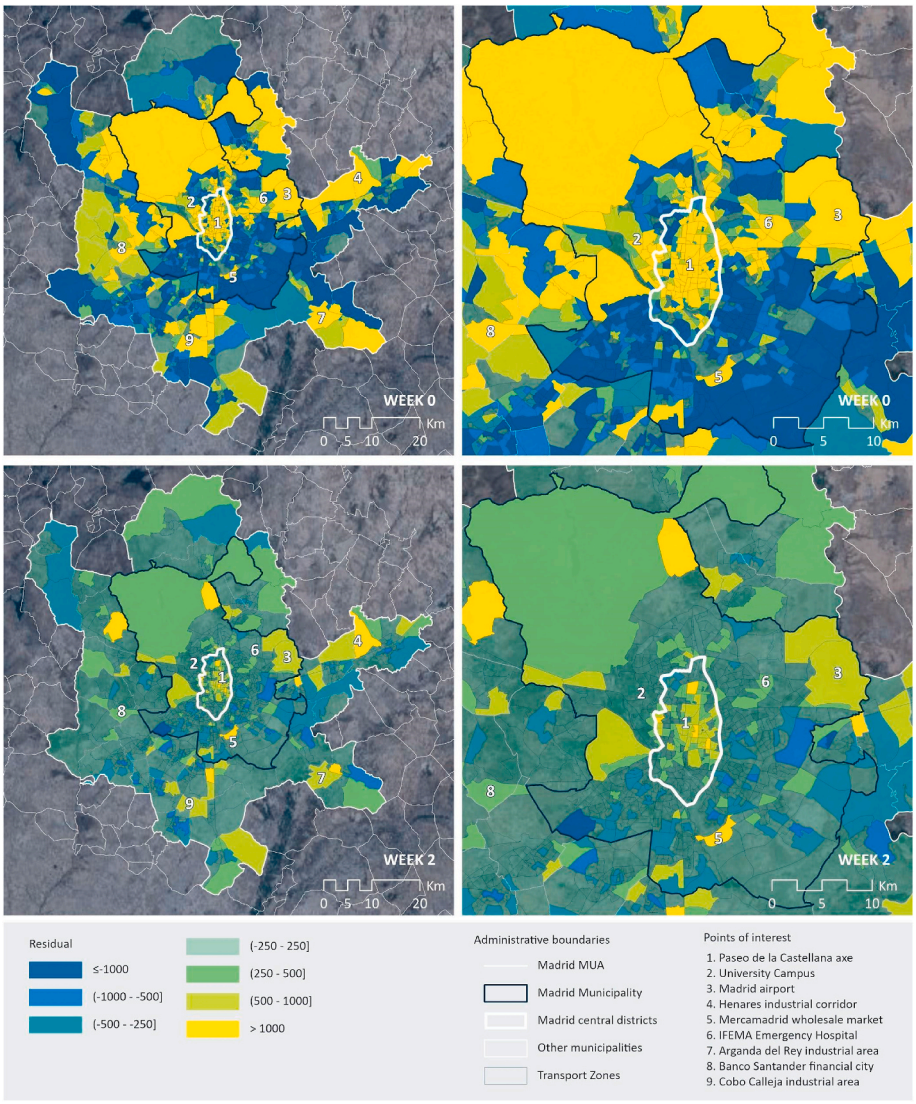


Fig. 3. Residuals in the bivariate correlations of the distribution of population at night and in the morning.

Table 5
Population distribution in the reference week and use of the predominant one.

Uses	Morning 08:00 to 14:00	Afternoon 14:00 to 19:00	Evening 19:00 to 22:00	Night 22:00 to 00:00	Census (02:00)**
Residential	3,848,781	3,932,847	4,136,932	4,244,711	4,272,127
Mixed residential	1,251,975	1,221,602	1,135,494	1,082,954	1,061,866
Activities	825,004	725,800	525,987	430,393	415,866
Total	5,891,478	5,847,032	5,767,322	5,727,775	5,719,651
Activities	**Morning**	**Afternoon**	**Evening**	**Night**	**Census**
Commercial	62,930	65,727	56,917	40,180	37,027
Cultural	11,214	9309	6011	4534	4054
Educational	66,949	54,536	32,305	24,064	24,298
Shows	18,055	18,415	22,477	17,416	13,194
Industrial	277,921	241,765	172,052	147,700	144,688
Offices	155,203	130,749	69,290	48,758	44,691
Parks and sports	59,288	52,842	39,716	33,269	33,036
Health	71,861	62,169	49,901	43,528	42,760
Transports	18,458	12,957	5638	2325	3314
Others	48,844	44,114	40,589	38,336	38,597
Total	825,004	725,800	525,987	430,393	415,866

with less intensity and also a smaller decline in the afternoon. However, during the pandemic, the three curves have tended to flatten, significantly reducing both the negative balances of residential spaces and the positive balances of mixed and activity spaces. Data also show the evolution of the different phases, with a flatter curve in the first and especially the week with the greatest restrictions (W2). With the closure

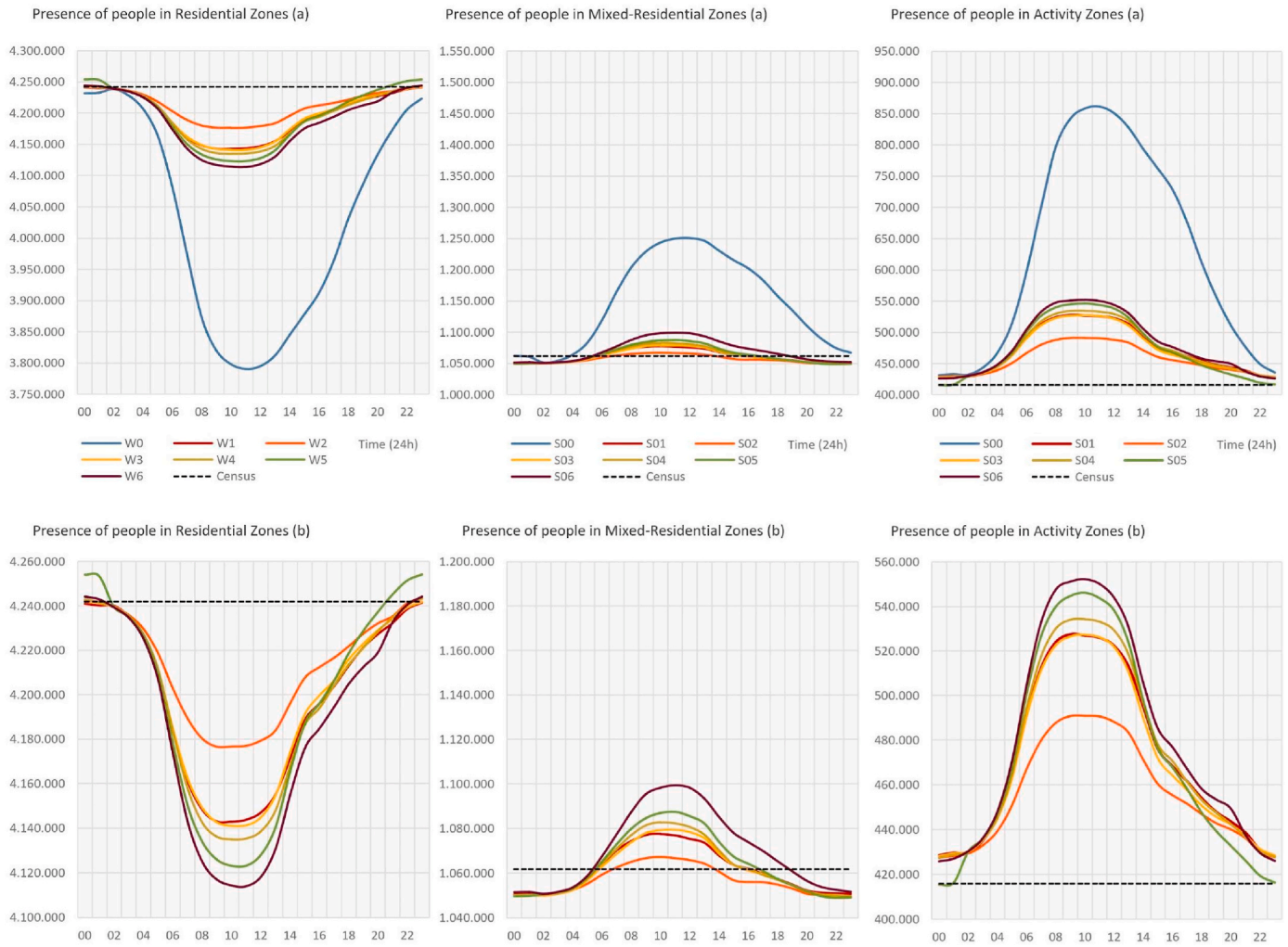


Fig. 4. Population distribution profiles throughout the day during the study weeks (W1–W6), including the reference week W0 (a) and without it (b).

of non-essential activities, imbalances were reduced by up to 85 % in residential spaces in the morning in week W2 (they lost only 63,000 people), by 90 % in the afternoon (with losses of only 34,000) and 100 % at night. These balances are reproduced inversely in the mixed and activity spaces. With the easing of the restrictions, profile curves and balances have been recovering, although activity spaces had a positive balance that represented only 28 % of the usual (W0) in the last week (W6).

The temporal distribution of the population in the activity areas shows different profiles and different behaviors during the study weeks according to the characteristics of their activity (Fig. 6). During the reference week (W0), the curves of office or industrial activities are very similar, however their behavior is different during the pandemic. Office workers have been able to implement teleworking to a greater extent, so that the presence of the population in these spaces has been reduced very significantly, to the point of practically flattening the profiles. However, industrial activities require the increased presence of workers, so profiles maintain a steeper curve. Another important factor is that in the industrial space there is a greater difference between weekly profiles (W2) and the rest of the weeks of the pandemic as a result of the closure of non-essential industrial activity during this period.

Among the rest of the activities, we see how large transport infrastructures (airport and railway stations), educational or health areas are activated especially in the morning, while commercial areas are activated somewhat more in the afternoon, and leisure and entertainment at night-time. However, all areas have significantly flattened their curves, especially in activities that have completely closed, such as education and entertainment, and to a lesser extent commerce, transport and health (Fig. 6).

3.3. Links between land use and population distribution

The results of the multiple regression models obtained for the different time slots show the close link between the spatial distribution of land use and the population in all time slots. The adjusted coefficients of determination were very similar and close to 0.7 in all time slots and weeks, and all have significant F-statistic values at the 0.000 level. No collinearity problems appeared in any of the models between the explanatory variables (VIF values less than 2 and tolerance greater than 0.6 in all cases). However, the models showed problems of spatial dependence. The distribution of the residuals was spatially autocorrelated (Moran's I error is statistically significant at the 0.05 level). Robust Lagrange Multiplier (error) was significant at the level of 5 %, while Robust Lagrange Multiplier (lag) values were significant in just one case.

Based on the OLS models obtained for the population distributions in a reference week W0, all variables have the expected signs (Table 6). During the morning, the residential and activity areas have positive signs (they tend to concentrate the population) and the distance to the center of Madrid has a negative sign (greater intensity of use in central spaces). The highest coefficients correspond to variables such as transport, culture, education and commerce, where there is very intensive use of the land (large population density per unit area), while they were



Fig. 5. Changes in the resident population in the census according to large land uses during the different study weeks (W0 – W6).

much lower in activities such as offices and, above all, industrial land. Throughout the day the coefficients of residential use are created, and the highest values are registered at night. Meanwhile, the coefficients decrease between morning and afternoon in all activities, except commercial ones, with higher values in evening. Evening and night-time variables such as offices and parks have negative signs, and educational and health uses at night are also negative. This has to do with the high mix of uses in the city and the weight of mixed residential areas, so that in these mixed-use zones the presence of activities reduces the potential presence of the population in these areas. Finally, the coefficient of the distance to the city center variable decreases throughout the day and ceases to be significant at night, showing the center-periphery gradient of activity, since the weight of residential use is greater in the periphery than in the center.

The spatial error models in the reference week (W0) during morning and afternoon are very similar to the OLS, with similar equations and slightly better fits (Table 7). However, the R^2 values increase in the evening and night. The coefficients of residential, industrial and commercial uses have values and trends similar to the results obtained in the OLS models. Nevertheless, during the evening, only land uses with positive signs are maintained and the distance to the center is no longer significant. At night, offices have negative sign, but a much lower coefficient than in the OLS model. The *LAMBDA* is significant at the level of 5 % in all models and grows from morning to night, showing a greater spatial dependence at night, when the spatial distribution of population is mainly explained by residential use.

The Spatial Error Models (SEMs) obtained for the weeks of the State of Alarm show similar coefficients and signs in all time slots, but with some nuances (Tables 8 and 9). In general, with the population confined to their homes and numerous activities closed, the equations tend to reproduce the situation occurring during the night of the reference week in all time slots. The residential land has similar coefficients in all weeks and all time slots, with a similar value to the one registered at night in week W0. Business activities, which have maintained a basic level, also show positive signs every week. However, their values are lower than those of night-time in a typical week, even in the morning, and they decrease throughout the day. Educational and park land, which have suffered a major closure, do not enter in the models. Offices have signs and values similar to the night of the reference week. Only industrial land has maintained positive signs in the morning. Finally, the variable *distance to the center* is not significant in any of the time slots.

The different phases followed in confinement also introduce significant nuances in the equations. In the week with the greatest restrictions (W2), the negative coefficients of activities such as offices are higher, and they decrease as the restrictions are lifted. Industrial activity, largely closed also during that W2 week, has a much lower coefficient during this week, while recovering in the weeks with the least restrictions (W4 and W6).

4. Conclusions

The expansion of the COVID-19 pandemic has led to a radical change in urban dynamics and the distribution of the population in relation to land uses throughout the day. The measures imposed to control the spread of the virus imply the total or partial closure of many urban activities, with direct repercussions on people's activity, their mobility and their distribution in the city. Knowing the keys to urban dynamics during lockdown phases and the restrictions imposed is essential for their management and a crucial element for containment against possible outbreaks or second waves. From this study, it is possible to draw some conclusions and contribute to this knowledge.

First, this paper shows that mobile phone data provides information with great potential for analyzing the impact of the measures taken regarding urban dynamics and the intensity of recovery in the different areas of the city after the lifting of restrictions. In this paper we have taken advantage of the high level of temporal detail of mobile data and have crossed them with information on land use with a high level of spatial and thematic disaggregation in order to determine how the restrictions imposed change the temporal profile of city use, with different impacts according to the types of activities present in some areas or

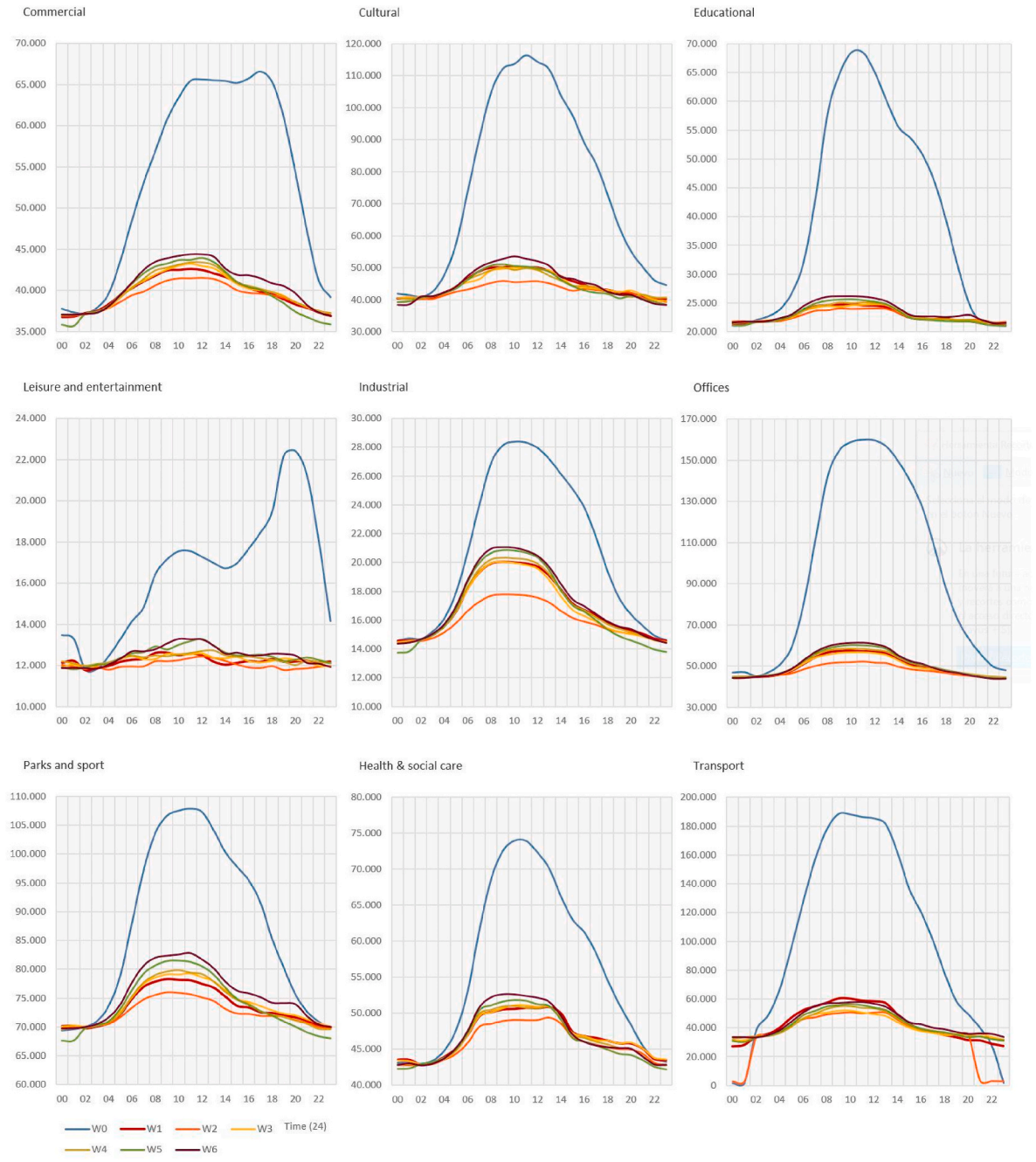


Fig. 6. Population distribution throughout the day in the different activity areas during the study weeks (W0–W6).

others.

Second, this research provides evidence of the different impact of the restrictions implemented on the city dynamics during the weeks of analysis, over the course of a typical day. More specifically, a first visual and dynamic analysis, through video-visualization, allowed us to explore the variation in population in the different urban areas throughout the day, comparing the reference week prior to the lockdown (W0) with that with the greatest restrictions on mobility (W2), showing very significant changes. A second analysis, based on the study of bivariate correlations of population distributions between large time slots, allowed us to obtain a numerical indicator to globally compare the impact of the lockdown measures in the different study weeks. The city of Madrid presents a high mix of land use, so that even in a reference week (W0) the correlations between the strips are very high. However, while in week W0 the correlations between morning and night decreased, due to the differences between residential and activity spaces, correlations were practically 1 during the lockdown, showing a similar distribution of the population in all time bands at night. The city turned off. The mapping of the residuals of these correlations showed that the few active zones during the morning hours were mainly logistics and industrial areas (positive residues).

Third, from the results obtained in this paper, it is possible to describe the different impact of the measures on the diverse areas of the city, characterized by its main land use (and therefore, also to evaluate the impact on the activities related to the different land uses). Through hourly population distribution profiles for the dominant land use in each zone, the study provides evidence of a ra°dical change with respect to the reference week (W0), especially in the weeks of greatest restrictions (W2). These profiles are simplified, since they consider only the dominant use, when in most areas there are several uses of the land. However,

Table 6
Regression models (OLS) in the reference week (W0).

	Morning		Afternoon		Evening		Night	
	B	Beta	B	Beta	B	Beta	B	Beta
(Constant)	1663.2**		1643.8**		1834,2**		1864,2**	
Residential [Ha]	110.6**	0.697	113.7**	0.725	118,1**	0,744	119,8**	0,737
Offices [Ha]	77.8**	0.122	47.3**	0.90	−46,5**	−0,087	−78,8**	−0,144
Industrial [Ha]	19.2**	0.069	11.3**	0.041				
Commercial [Ha]	111.6**	0.117	125.8**	0133	125,4**	0,131	83,9**	0,086
Educational [Ha]	125.2**	0.083	74.2**	0.50			−70,0**	−0,045
Cultural [Ha]	143.9**	0.075	104.1**	0.055				
Transports [Ha]	218.1**	0.058	139.6**	0.037				
Health [Ha]							−49,9*	−0,029
Parks and sports [Ha]					−2,5*	−0,029	−4,0*	−0,044
Others [Ha]	80.2**	0.122	71.9**	0.111	69,9**	0,106	69,8**	0,104
Distance [km]	−29.7**	−0.072	−22.8**	−0.056	−12,9*	−0,031		
No. Observations	1062		1062		1062		1062	
R^2	0.674		0.690		0.694		0.686	
Adj. R^2	0.671		0.688		0.692		0.684	
AIC	19397.3		19318.1		19324.8		19403.5	
Moran's I (error)	6.845**		8.045**		14.334**		17,654**	
Lagrange Mult. (lag)	24.533**		21.027**		45.903**		68.473**	
Robust LM (lag)	4.409**		1.175		0.029		0.960	
LM (error)	41.527**		57.974**		190.118**		296.986**	
Robust LM (error)	21.403**		38.122**		144.245**		229.473**	
LM (SARMA)	45.936**		59.149**		190.150**		297.946**	

**Significant at the 0.05 level; * Significant at the 0.10 level.

Table 7
Spatial Error models (SEMs) in the reference week (W0).

	Morning		Afternoon		Evening		Night	
	B	Std.Error	B	Std.Error	B	Std.Error	B	Std.Error
(Constant)	1771.0**	188.8	1742.9**	189.4	1701.2**	147.5	1751.7**	163.9
Residential [Ha]	111.3**	3.5	114.5**	3.4	119.0**	2.8	121.0**	2.98
Offices [Ha]	76.1**	11.3	52.2**	10.8			−31.6**	10.0
Industrial [Ha]	21.6**	5.3	14.1**	5.0				
Commercial [Ha]	104.4**	17.6	114.5**	16.8	99.8**	15.8	74.5**	15.9
Educational [Ha]	119.7**	27.8	75.4**	26.7				
Cultural [Ha]	132.3**	35.5	100.6**	33.8				
Transports [Ha]	214.2**	64.3	145.5**	61.1				
Health [Ha]								
Parks and sports [Ha]								
Others [Ha]	61.3**	15.3	51.3**	14.6	36.8**	12.4	43.0**	13.7
Distance [km]	−31.1**	11.96	−24.2**	10.2				
LAMBDA	0.283**	0.071	0.472**	0.06	0.513**	0.037	0.577**	0.03
No. Observations	1062		1062		1062		1062	
R^2	0.688		0.710		0.743		0.756	
AIC	19362.4		19268.4		19184		19200	

**Significant at the 0.05 level; * Significant at the 0.10 level.

the results explicitly showed the drastic reduction in population in activity spaces in the morning and afternoon, while residential spaces conserve the population in those time bands. All profile curves tended to flatten significantly, but once again the activities related to industry, commerce or health maintained more active profiles, compared to very subdued educational, leisure or office areas.

Finally, this research provides evidence of the close link between the presence of people and the spatial distribution of the different land uses in all time slots of the different weeks of study. Unlike the profiles, the multiple regression analysis allowed us to consider the influence of the different land uses of each zone by the population and not to work only with the dominant use. In the reference week (W0) the coefficients of the independent variables showed the expected signs, positive in the variables of land use and negative in the distance to the center. In that week (W0), the variation of the coefficients throughout the day was consistent: increasing for residential and commercial land (except at night), and decreasing for the rest of the activities. Some land uses, such as offices, education, health or parks had negative signs at night, as a result of the high mix of uses in the city and the weight of mixed residential areas. In these mixed-use areas, the presence of activities reduces the potential presence of the population in these mostly residential areas. During the lockdown weeks, the equations tend to reproduce the nighttime situation of the reference week (W0) for any period of the day. Only basic activities, such as commerce, have been active in all time frames of the day, but now with higher coefficients in the morning. Industry has also maintained some activity, but only in the morning and in the weeks of less restriction. Meanwhile, activities such as offices, education or parks showed negative signs in all time slots and in all weeks of the pandemic.

This research does not explore the expected relationship between mobility restrictions and the pandemic spread. Although this is a crucial topic, it is out of the scope of the paper. This study aims at providing useful information for pandemic management and post-recovery planning, focusing on the impact of mobility restrictions across the city. In the first place, it enables us to improve our knowledge of urban dynamics during each of the confinement phases and the degree of restricted mobility of the population. Changes in population density according to mobility restrictions help to assess the level of follow-up of

Table 8
Spatial Error models during the weeks of confinement (morning and afternoon).

	Morning				Afternoon			
	B – W1	B – W2	B – W4	B – W6	B – W1	B – W2	B – W4	B – W6
(Constant)	1709.8**	1742.3**	1694.8**	1678.5**	1767.1**	1770.2**	1759.7**	1748.5**
Residential [Ha]	120.8**	120.3**	121.0**	120.9**	120.4**	120.5**	120.5**	120.8**
Offices [Ha]	−24.9**	−28.4**	−25.5**	−23.6**	−24.8**	−28.1**	−24.9**	−23.9**
Industrial [Ha]	15.1**	9.0*	15.8**	18.0**				
Commercial [Ha]	73.6**	72.3**	74.5**	76.2**	72.2**	70.8**	72.7**	74.6**
Educational [Ha]								
Cultural [Ha]								
Transports [Ha]								
Health [Ha]								
Parks [Ha]								
Other [Ha]	41.3**	42.6**	42.7**	44.3**	40.0**	41.2**	40.9**	40.8**
Distance [km]								
LAMBDA	0.542**	0.568**	0.530**	0.518**	0.568**	0.579**	0.565**	0.554**
No. Observations	1062	1062	1062	1062	1062	1062	1062	1062
R^2	0.751	0.752	0.753	0.754	0.753	0.754	0.754	0.757
AIC	19146	19173	19132	19115	19178	19186	19171	19152

**Significant at the 0.05 level; * Significant at the 0.10 level.

Table 9
Regression models (Spatial Error) during the weeks of confinement (evening and night).

	Evening				Night			
	B – W1	B – W2	B – W4	B – W6	B – W1	B – W2	B – W4	B – W6
(Constant)	1768.1**	1768.1**	1762.7**	1766**	1761**	1763.3**	1757**	1762.3**
Residential [Ha]	120.9**	121.1**	121.0**	121.0**	121.5**	121.5**	121.5**	121.6**
Offices [Ha]	−30.8**	−31.4**	−30.8**	−30.9**	−32.9**	−32.6**	−32.6**	−33.6**
Industrial [Ha]								
Commercial [Ha]	69.8**	68.9**	69.9**	70.7**	68.2**	68.1**	68.3**	67.1**
Educational [Ha]								
Cultural [Ha]								
Transports [Ha]								
Health [Ha]								
Parks [Ha]								
Other [Ha]	41.8**	41.5**	41.8**	41.3**	41.9**	40.9**	41.8**	42.3**
Distance [km]								
LAMBDA	0.587**	0.591**	0.588**	0.585**	0.597**	0.599**	0.598**	0.597**
No. Observations	1062	1062	1062	1062	1062	1062	1062	1062
R^2	0.754	0.756	0.755	0.757	0.756	0.757	0.757	0.757
AIC	19203	19199	19201	19186	19213	19234	19210	19208

**Significant at the 0.05 level; * Significant at the 0.10 level.

the measures. Second, it helps us to determine in which spaces and activities a greater presence of the population is concentrated during the weeks with restrictions and those when the restrictions are lifted. This is of interest to identify the areas of the city, the activities and the population groups associated with them, which remain functional and, consequently, pose a greater risk of virus transmission. In addition, once the restrictions are lifted, these analyses performed are able to show the pace of the city's recovery and the different recovery speeds of each urban activity.

CRediT authorship contribution statement

Gustavo Romanillos: Conceptualization, Methodology, Visualization, Writing – review & editing. **Juan Carlos García-Palomares:** Conceptualization, Methodology, Visualization, Writing – review & editing. **Borja Moya-Gómez:** Conceptualization, Methodology, Visualization, Writing – review & editing. **Javier Gutiérrez:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Javier Torres:** Data curation, Conceptualization, Methodology, Writing – review & editing. **Mario López:** Data curation, Conceptualization, Methodology, Writing – review & editing. **Oliva G. Cantú-Ros:** Data curation, Conceptualization, Methodology, Writing – review & editing. **Ricardo Herranz:** Data curation, Conceptualization, Methodology, Writing – review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2021.102524.

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