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ORIGINAL ARTICLE

Uncovering spatiotemporal micromobility patterns through the lens of space–time cubes and GIS tools

Daniela Arias-Molinares[1] · **Juan Carlos García-Palomares**[1] · **Gustavo Romanillos**[1] · **Javier Gutiérrez**[1]

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Abstract
In the past ten years, cities have experienced a burst of micromobility services as they offer a flexible transport option that allows users to cover short trips or the first/last mile of longer trips. Despite their potential impacts on mobility and the fact that they offer a cleaner, more environmentally friendly alternative to private cars, few efforts have been devoted to studying patterns of use. In this paper we introduce new ways of visualizing and understanding spatiotemporal patterns of micromobility in Madrid based on the conceptual framework of Time-Geography. Hägerstrand's perspectives are taken and adapted to analyze data regarding use of micromobility, considering each trip departure location (origins) obtained from GPS records. The datasets are collected by three of the most important micromobility operators in the city. Trip origins (points) are processed and visualized using space–time cubes and then spatially analyzed in a GIS environment. The results of this analysis help to identify the landscape of micromobility in the city, detecting hotspot areas and location clusters that share similar behavior throughout space and time in terms of micromobility departures. The methods presented can have application in other cities and could offer insights for transport planners and micromobility operators to better inform urban planning and transportation policy. Additionally, the information could help operators to optimize vehicle redistribution and maintenance/recharging tasks, reducing congestion and increasing efficiency.

Keywords Micromobility · Space–time cubes · GIS · Time series · Hotspot · Clustering

JEL Classification O18 · R41 · C23 · C29 · C38

✉ Juan Carlos García-Palomares
jcgarcia@ucm.es

[1] tGIS Research Group, Department of Geography, Complutense University Madrid, Madrid, Spain

1 Introduction

The introduction of the sharing economy has impacted many economic sectors, including transportation. New services, like micromobility, are offered each day and users have access to multiple transport options, radically changing their travel behavior (Jiao and Bai 2020). Micromobility has been defined as the short-term access to low-speed shared vehicles, according to the user's needs and convenience, instead of requiring vehicle ownership (Lazarus et al. 2020; Shaheen and Cohen 2019). In the past decade, micromobility services have gained attention as they are changing urban mobility dynamics by offering a flexible transport option capable of avoiding road congestion, reducing the required parking space, and lowering noise/air pollution, since all vehicles are hybrid electric/electric, as well as reducing inequities in the provision of transportation services and encouraging intermodality with mass transit (Aguilera-García et al. 2020; Arias-Molinares et al. 2021; Desjardins et al. 2022).

The growth of micromobility services has been enabled by the rapid development of information and communication technologies (ICTs), along with improvements in Geographical Information Systems (GIS), the emergence of new data sources, and advanced data processing capabilities using programming. Individuals now move using the latest location-aware technology, which requires data that fits personal needs. As a result, fundamental questions related to geospatial data such as "what?," "where?" and "when?" are increasingly relevant (Kraak 2003). New technologies generate a huge amounts of data with high spatiotemporal detail, all of which explains the revival and growing interest in Hägerstrand's Time Geography (Miller 2005; Shen et al. 2013; Dodge and Nelson 2023; Shaw 2023).

The time-geographic framework proposed by Hägerstrand (1970) at the end of the sixties provided a useful means for exploring the spatiotemporal component of the human activity. However, when this model was introduced, the available data and the tools for its visualization and analysis were scarce. Therefore, despite its usefulness, only a few studies implemented time-geographical visualizations using empirical data up until the mid-1990s (Kwan 2004). Today's software's advanced capabilities and the increasing availability of geo-referenced data collected by global positioning systems (GPS) offer high spatiotemporal granularity which enables, more than ever before, the operationalization and implementation of time-geographic constructs in multiple research areas like crime, public health, traffic safety, and construction (Desjardins et al. 2020; Jing et al. 2020; Nakaya 2010; Yang et al. 2017; Roofagari-Esfahan et al. 2015).

Transport planning is one area with potential application for Time Geography (Miller 2007). Studies related to the use of space–time paths (st-paths) include Osorio-Arjona and García-Palomares (2020), Shaw and Wang (2000) and Frihida and Marceau (2004) that delved into the spatiotemporal characteristics of travel patterns or Kapler and Wright (2005) and Kraak and He (2009) that included novelties in annotations and the incorporation of icons/images to describe the activities related to the movements. To explore and process large datasets, Shaw et al.

(2008) proposed a generalized method for st-paths to explore temporal changes among individuals. Other studies used prims to understand space–time accessibilities and analyze complex activities (Huisman and Forer 1998, 1999; Miller 1999; Dijst and Vidakovic 2000; O'Sullivan et al. 2000; Hornsby and Egenhofer 2002; Timmermans et al. 2002; Jacquez et al. 2005; Miller 2005; Ratcliffe 2006; Kuijpers and Othman 2009; Neutens 2010; Kuijpers et al. 2011).

All these previously mentioned studies applied Hägerstrand's concepts to their topics of interest, as they analyzed *people's movements*. In this paper, draw inspiration from concepts and tools from Time-Geography to propose innovative ways of visualizing massive micromobility data. Therefore, we continue the line of research set, for example, in Yang et al. (2020) that proposed a space–time demand cube framework to represent and capture the fine-grained spatiotemporal variations in bike demand using GPS records from a dockless bike-sharing operator in China. They used space–time cubes to aggregate trip origins which helped them to visualize and understand historical and dynamic bike demands. Another example is found in Pereira et al. (2022), that took the space–time path idea and created a package called "{gtfs2gps}" which helps to easily process static GTFS and visualize trajectories of public transport vehicles at fine spatial and temporal resolutions. Instead of working with an individual's path, they graphed bus routes. They explored the boarding/alighting of passengers as 'fixed activities' that occur at public transport stations. As a result, they obtained a graphic visualization of each route's trip frequency in a 3D space–time aquarium with a sequence of space–time paths, one for each trip, stacked over time. On both studies, Time Geography represents the base from which they take off and delve into new ways of visualizing mobility data, which is the aim of this paper.

Using this approach, we try to address the need to understand the space–time logic of the use of micromobility tools, and how this logic impacts micromobility's operational tasks, as well as the opportunity to analyze demand patterns with more spatiotemporal detail. We can use space–time cubes (STC) to visualize and analyze the spatiotemporal distribution of micromobility supply and, consequently, its impact on the urban landscape and the new challenges it generates (parking space needed and conflicts with pedestrians, competition with other modes, etc.). Additionally, we can investigate the spatiotemporal capability constraints between supply (distribution of vehicles) and demand (through land uses).

Hence, our study aims at contributing to the literature that explores micromobility spatiotemporal travel patterns using GPS records and space–time cubes. More specifically, using GPS origin point records from three different shared modes (bikes, mopeds and scooters), we intend to identify the most important hotspot areas, analyze trip generations according to the time of the day and finally, be able to identify different types of areas (location clusters) that share similar behavior in space and time in terms of micromobility departures. We believe that these types of studies are necessary and more feasible nowadays with the new available sources of massive data, that are allowing researchers to go beyond what has been done traditionally, and rather innovating in new approaches to address mobility issues. Transport authorities and micromobility operators could feed their decision-making processes with insights obtained from understanding spatiotemporal patterns from a space–time perspective. The rest of the article is structured in four sections. Section 2 summarizes related literature, while Sect. 3 introduces the study case, data and methods used, following Sect. 4 with results and lastly Sect. 5 offers discussion and conclusions.

2 Literature review

2.1 Research on micromobility's spatiotemporal patterns

In the last decade, there has been a growing body of literature related to studying spatiotemporal travel patterns for shared mobility and micromobility services, especially bike-sharing programs as they were the first schemes deployed. For example, Corcoran et al. (2014) used GPS data and explored the effects of weather and calendar events on spatiotemporal patterns of bike-sharing using multivariate regression models. Another similar study conducted by Purnama and Irawan (2018) also analyzed GPS records from the public bike-sharing system in London and New York and use the Pearson's correlation coefficient to observe the correlation of external factors with the daily usage. Similarly, Nickkar et al. (2019) used GPS records to study the influence of socio-demographic factors on travel patterns in Baltimore and evaluated the relationship between gender and land use in terms of the trip's origin and destination locations by using statistical analysis.

More recently, with the introduction of new micromobility modes like mopeds and scooters, more studies have become available regarding comparative analyses between existing bike-sharing schemes and moped-style or scooter-sharing ones. One of these studies, conducted by Zhu et al. (2020) compared dockless bike-sharing and station-based scooter-sharing services using GPS records (for bikes) and a scraping tool (for scooters) to estimate redistribution trips and fleet sizes as well as other descriptive characteristics that help understand the heterogeneity of the two services. Moreover, Younes et al. (2020) used open-access Application Programming Interfaces (APIs) for six dockless scooter-sharing services and historical trip data for the city's public bike-sharing service (Capital Bikeshare, Washington DC) to estimate two variables: hourly number of trips and hourly median duration of trips. This estimation was based on a negative-binomial regression model including environmental and economic variables such as weather-related data, gasoline prices, local events or disturbances, day of the week, and time of day. Regarding moped-style scooter-sharing services (also known as moto-sharing), four recent studies are found. One of them by Pérez-Fernández and García-Palomares (2021) that used GPS datasets and proposed a methodology to locate parking places based on the varying distribution of demand over the day. Jiao and Bai (2020) applied univariate LISA to identify areas of high demand (hotspots) in the use of shared e-scooters, as a preliminary step before applying regression models. Moreover, Arias-Molinares et al. (2021) also used mopeds' trip data to analyze locational patterns over time and assess how the different factors influenced its usage level and self-balance potential using Exploratory Spatial Data Analysis (ESDA) tools. And lastly, Bach et al. (2023) examined the determinants of the spatial coverage of four moped-style scooter-sharing services in Barcelona. Their results suggest that territorial coverage is defined by centrality, household disposable income, and topography, with low-accessibility areas consistently omitted from services. Based on previous literature, our main contribution is the comparison of spatiotemporal patterns of three different micromobility modes simultaneously (docked bikes and dockless scooters and mopeds). These analyses offer useful insights into similarities and differences in the usage patterns of these systems across different parts of Madrid, over different hours of the day, according to weekdays and weekends, and how they relate to land use.

2.2 Building upon the ideas of time geography to create new ways of visualizing micromobility data

We link Time Geography and micromobility data with the offer of a potential tool for processing and visualizing massive amounts of data, especially GPS records. As stated by Pereira et al. (2022), space–time cubes make it possible to visualize and explore mobility data in ways that they were not easily done before. We depart from the fact that micromobility services are filling the gap or being breach modes between walking and motorized transport alternatives. With shared services, users have now the alternative to not walk and neither use a motorized transport, but rather use an eco-friendly option like a bike, moped or scooter that has no CO_2 emissions and allows faster speeds (with respect to walking). But for a micromobility trip to even occur, an individual has to both, be located inside a service area and also find an available shared vehicle. Therefore, we focus on the *access to these shared services* which are represented by the occurrence of a *trip departure*, which are the places where these two conditions were fulfilled. By aggregating trip origins into space–time cubes, we visualize the access locations to shared services and its spatiotemporal patterns over time. Based on the notion of stationary activities, trip departures constitute the locations where an individual spent some time in order to locate, reserve and initiate a shared mobility trip. These departures are also sparsely distributed in space and time, where the fleet is available, being also related to the service's constraints. Thus, micromobility could be perceived as a subject to authority restrictions as each service have specific areas of coverage (service geo-fence). Its capacity as a mobility service is limited by the number of vehicles (fleet size), the distance that can be traveled (mostly short trips), and its geographical distribution throughout the day. Finally, the system's success depends on the coupling of the vehicles' location and its demand, and thus, the redistribution of vehicles becomes one of the most fundamental elements to consider.

Continuing with this line of research, we intend to explore how spatiotemporal dynamics change over a day (hourly), according to different types of days (weekdays and weekends), and how these dynamics are linked to land uses. Additionally, we will conduct these analyses not only regarding bikes but also other micromobility services like shared mopeds and scooters so that comparisons are allowed. We believe space–time cubes are a useful tool to study aggregated micromobility patterns because it offers a better overall understanding of the spatiotemporal patterns in large datasets, enabling researchers to quickly identify the most relevant changes in dynamics along space and time, which becomes a harder task to do by only using traditional 2D maps.

3 Study context, data and methodology

3.1 Study context

The selection of Madrid is of special interest as the city has been known as one of Europe's top living laboratories for shared mobility, allowing its residents to be familiar with the emerging transport options, especially micromobility services (Aguilera-García et al. 2020). The multiple and varied shared mobility supply, along with a solid public transport system, a great land use diversity and high population/employment densities make Madrid an appropriate area for these new services to burst. In 2019, the shared fleet was estimated in more than 20.000 vehicles (Arias-Molinares and García-Palomares 2020; Bernardo 2019; Granda and Sobrino 2019). These services are usually supported by mobile applications where their clients register and locate vehicles. In the case of Madrid, all micromobility services offer electric vehicles and can be station-based or dockless models. For our research, we have established collaboration agreements with two of the most important micromobility operators in Madrid to access anonymized trip data: *Movo* and *Muving*. In the case of *BiciMAD*, the data are publicly shared through an open data portal. Station-based services like *BiciMAD* have designated locations where users pick and leave the vehicles at, while dockless services, like *Movo* and *Muving,* offer more flexibility as the vehicles can be picked/returned at any location within a geographic area (also known as geo-fence).

BiciMAD is Madrid's public bike-sharing system, in operation since 2014, and currently being managed by Municipal Transport Company (EMT), with around 75.000 subscribers (Ayuntamiento de Madrid 2019). Since its launch in 2014, four expansions have taken place and it now has 264 stations with a total of 2.900 bikes. All BiciMAD's fleet is equipped with GPS trackers and pedal assistance up to 25 km/h. BiciMAD is one of the first micromobility services deployed in the city and the one managed by a public transport authority. Secondly, Movo is a moped-style scooter-sharing (also known as moto-sharing) and scooter-sharing service launched in 2018 and it operates 500 mopeds and 1.400 scooters (Polo and González 2019). Finally, Muving is a moped-style scooter-sharing operator that manages 755 mopeds. The company was operative in Madrid from 2018 to 2020 (Arias-Molinares et al. 2021) (see Fig. 1).

One of the aspects that most differentiates these services is their area of coverage (geo-fence), which is closely related to their different models. In the case of BiciMAD, being a station-based model, it covers essentially the city's core center area (inside M-30 Highway) where most bike stations are located. As there are specifically designated areas, BiciMAD's usage is more intense and concentrated around these locations. In the case of dockless services, the geo-fence is larger reaching other peripheral areas outside the M-30 highway and being more homogeneously distributed in the city which creates a relatively less intense usage in

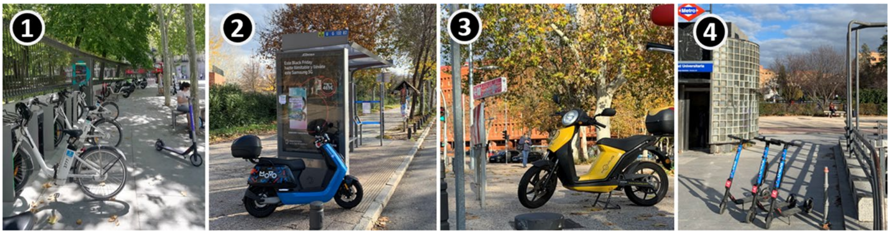

Fig. 1 Micromobility services analyzed in the study. From left to right: (1) Station-based bike-sharing (BiciMAD bikes), (2 and 3) dockless moped-style scooter-sharing (Movo and Muving mopeds) and 4) dockless scooter-sharing (Movo scooters)

each location. This study performs the spatiotemporal analyses of each service considering these different geo-fences, not according to a single area of coverage.

3.2 Data

As was mentioned previously, collaboration agreements were established with the companies named "Movo" (mopeds + scooters) and "Muving" (mopeds). In the case of "BiciMAD" (bikes), this was not necessary because they publicly share their data on their website. We obtained datasets for Movo and Muving covering the months from the last semester of 2019 (from June to December), thus the same period was downloaded for BiciMAD to cover the same timeframe for all the services evaluated.

- *BiciMAD* data were extracted from the website: https://opendata.emtmadrid.es/Datos-estaticos/Datos-generales-(1). They monthly upload datasets (in JSON format). BiciMAD datasets offer the origin location (point with XY coordinates) of each trip and the exact time when it started (timestamp). It also offers information on trip time (seconds). Only BiciMAD separates those origins of administrative trips (redistribution of vehicles) which is highly useful to filter data.
- *Movo* the company provided us with a dataset (in JSON format). Movo datasets offer information of the original location (point with XY coordinates) of each trip, the time when it started (timestamp), and the vehicle type (moped/scooter). It also offers information on trip time (seconds).
- *Muving* the company provided us with a dataset (in CSV format). Muving datasets offer information of the original location (point with XY coordinates) of each trip and the time when it started (timestamp). It also has information on the trip time (minutes) and distance (km).
- Land use data and transport zone data: to perform certain spatial analyses, we use land use data provided by the Directorate-General for Cadastre in Spain (Cadastre), by a built entity of the study area. The databases define the surface area [m2] of each type of land use. These data are updated every six months and the data set used corresponds to the update of January 24, 2020.

3.3 Methodology

3.3.1 Processing and cleaning the datasets

The data processing workflow covered entering, cleaning, transforming, and outputting the final valid datasets (using Python vs. 3.8). For all the datasets, the initial cleaning process involved eliminating those observations (origin points) with trip distance or time equal to zero (erratic data). A second cleaning stage consisted of filtering datasets by making certain assumptions, such as not considering the origins of trips that lasted over a certain time or cover large distances (as seen in the filtering criterion in Table 1). This was necessary to eliminate unrealistically long-distance trips (probably GPS errors) and redistribution trips (as only BiciMAD tagged them). Thus, we cleaned BiciMAD and Movo datasets by trip time and in the case of Muving, we cleaned the dataset by both trip time and distance.

After obtaining the cleaned datasets for all services (bikes, mopeds and scooters), we decided to separate the databases according to different scenarios based on the day of the week: weekdays (from Mondays to Fridays) and weekends (Saturdays and Sundays). We also determined to work with the count of origin points for an average day. Therefore, we divided the weekdays databases by 120 (5 days * 4 weeks * 6 months = 120 weekdays in 6 months) and the weekends databases by 48 (2 days *4 weeks * 6 months = 48 weekends in the same period).

3.3.2 Understanding spatiotemporal travel patterns

Once our cleaned and averaged datasets were obtained, we visualize and analyze origins (departures) using STC. Geography was represented according to a hexagonal grid (with a centroid-to-centroid distance equal to 250 m that covers the study area, while the height was representing each hour of the day. A 250 m-sided hexagonal grid was determined based on similar research as this size ensures that each cell contains several city blocks (García-Palomares et al. 2015; Degele et al. 2018; McKenzie 2019b; Megler et al. 2014; Barros et al.

Table 1 Filtering criterion for the second stage of dataset cleaning

Variable	Min value	Max value	Filtering criterion
Time	60 s	2 h	Min value: trip duration longer than one minute was kept in our study dataset (McKenzie 2019b). Trips with a duration less than 60 s are probably cases of users that had problems with the vehicle/app Max value: two hours is the maximum battery life of an electric vehicle given continuous movement. Any trip lasting longer than two hours implies that the vehicle was offline for some period (i.e., recharging or in a truck for relocation)
Distance	100 m	70 km	Min value: only those trips with a road network distance greater than 100 m were kept (McKenzie 2019b) Max value: mostly, micromobility vehicles' autonomy is 70 km

2020). Following this scheme (see Fig. 2), when creating the STCs, we aggregate each origin (departure point) to the correspondent bin (hexagons and hour) when the trip was initiated. STCs were then created for weekdays and weekends. This step results in the creation of six cubes: bikes-weekdays, bikes-weekends, mopeds-weekdays, mopeds-weekends, scooters-weekdays, and scooters-weekends, which are the input layers for the rest of the analyses, performed with ArcGIS Pro version 2.8.3.

With the STCs created, the first analysis intends to capture micromobility's different dynamics with two complemental visualizations: daily (2D maps) and hourly (3D maps) behavior. For 2D visualizations, we make a map representing the total amount of departures (origin points) by hexagon according to the day of the week and mode. In the case of 3D visualizations, two STCs are created. The first one shows hourly departures (origin points) hourly, while the other represents the hot and cold spot analyses hourly, using Getis-Ord's index (Gi). This statistic measures the degree of clustering for either high or low values. The resultant *z*-scores and *p*-values report where features (in this case hexagons) with either high or low values are clustering spatially. This method analyses each feature within the context of neighboring features, for which we determined a 500 m distance band, as it will include all the neighbors surrounding each hexagonal cell and based on similar previous research (García-Palomares et al 2015). For both 3D visualizations, and due to space reasons, we determined to show results at certain relevant hours (instead of all hours), which helped to understand and highlight important dynamics throughout the day: 00 h (majority of people at home or nightlife activities), 08 h (rush peak AM hour), 14 h (lunch and midday activities) and 19 h (rush peak PM hour and nightlife activities) (as we can observe and justify by Fig. 4). Finally, the results of Hotspot Analysis by each hour are summarized in a 2D map that represents the percentage of times that each hexagon was a hotspot throughout the day.

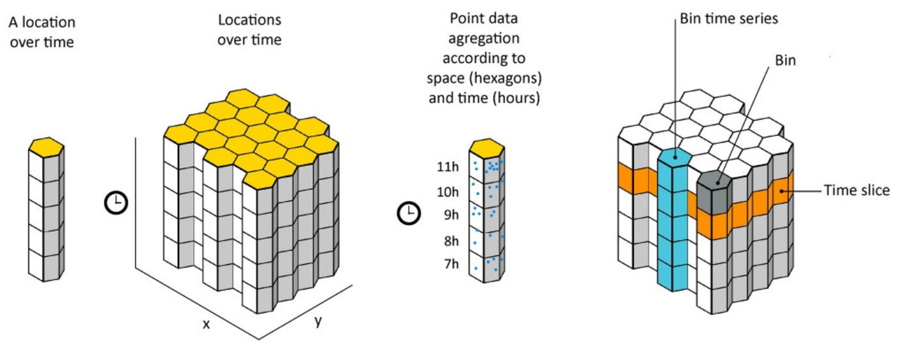

Fig. 2 Space–time cube models' scheme

3.3.3 Identifying locations that share similar travel behavior

The second analysis intends to identify and group locations that shared similar space–time behavior in terms of micromobility's departures. This helps to categorize types of spaces obtaining what we called "location profile-time clusters". To this end, we used Time-Series Clustering, which is the process of partitioning a time-series dataset into a certain number of clusters, according to a certain similarity criterion (Huang et al. 2020). Clustering is a data mining technique in which similar data is placed into related/homogeneous groups without knowing the group's definition. More specifically, clusters are formed by grouping objects that have maximum similarity with other objects within the group and minimum similarity with objects outside the group (Aghabozorgi et al. 2015). A special type of clustering is time-series clustering. A sequence composed of a series of nominal symbols from a particular alphabet is usually called a *temporal sequence*, while a sequence of continuous, real-valued elements is known as a *time series.* A time series is dynamic because its feature values change as a function of time, which means that the value(s) of each point of a time series is/are one or more observations that are made chronologically. Hence, time series are a type of temporal data which is high dimensional and large in data size (Keogh and Shruti 2003; Rani and Sikka 2012; Warren-Liao 2005; Aghabozorgi et al. 2015). The Time-Series Clustering method identifies the locations in a space–time cube that are most similar and partitions them into distinct clusters in which members of each cluster have similar time-series characteristics. These techniques have been applied in several research (Mattera 2022; Li and Xu 2021; Wang et al. 2021; Aghabozorgi et al. 2015). Time series can be clustered, so they have similar values across time, stay in proportion across time, or display similar smooth periodic patterns across time. This latter one is the Profile (Fourier) type, and it is used to cluster time series that have similar smooth, periodic patterns in their values across time. These periods are sometimes called cycles or seasons, and they represent the durations of a single pattern that then repeats in a new period. As micromobility services follow repetitive seasonal trends, we determined to use this approach.

The cluster results finally help us to explore the relationship between the types of locations (profile-time clusters) and land use. To that end, we first identify the predominant land use in each hexagon in Madrid. The predominant land use was then grouped into three generic land uses, according to cadastral data: 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, i.e., offices, industry, retail or education) and mixed residential (all other cases). Finally, the spatial intersection of the resulted types of locations with this generic land use information enabled us to obtain the number of hexagons that represent a certain type of profile-time cluster and that are located at certain land use. This analysis resulted in a summary table indicating the percentage of hexagons for each type of land use according to clusters.

4 Results

4.1 General patterns

Table 2 summarizes the main characteristics of the datasets analyzed. As it can be seen, bikes are the most important shared mode with the highest departures (origin points). To grasp bikes' importance, we can state that for every person that took a moped or scooter to travel during weekdays in 2019, there were approximately four and 24 people respectively, taking a bike. For weekends, however, the difference is slightly reduced as for every person taking a moped or scooter, approximately three and 18 people were taking a bike respectively. When identifying the days of the week with the highest departure counts, bikes are mostly used on Tuesdays while the dockless modes are mostly used toward the weekends on Thursdays (in the case of scooters) and Fridays (for mopeds). Preferred hours are also different for station-based and dockless services as BiciMAD's peak hour is at 17 h while in the case of both dockless services, peaks are shown at 19 h. These preferred days and hours for the different services could suggest that station-based bikes are mostly being used for commuting or conducting routinary

Table 2 Descriptive characteristics of the datasets analyzed for micromobility services

Characteristic	Bikes	Mopeds	Scooters
Weekdays			
Total departures	1,311,372	329,094	55,242
Departures on an average day	10,928	2,742	460
Departures in peak day of week	274,499 (Tuesday)	71,729 (Friday)	11,733 (Thursday)
Departures in peak hour	94,740 (17 h)	26,410 (19 h)	4,944 (19 h)
Average departures by hour	455	114	19
Standard deviation	260	71	15
Coefficient of variation	57	62	79
Max	790	220	41
Min	43	9	1
Weekends			
Total departures	311,589	111,427	17,746
Departures on an average day	6,491	2,321	370
Departures in peak day of week	167,337 (Saturday)	60,899 (Saturday)	9,356 (Saturday)
Departures in peak hour	19,784 (18 h)	8,270 (20 h)	1,500 (19 h)
Average departures by hour	271	97	15
Standard deviation	105	48	11
Coefficient of variation	39	49	73
Max	412	172	31
Min	79	17	2

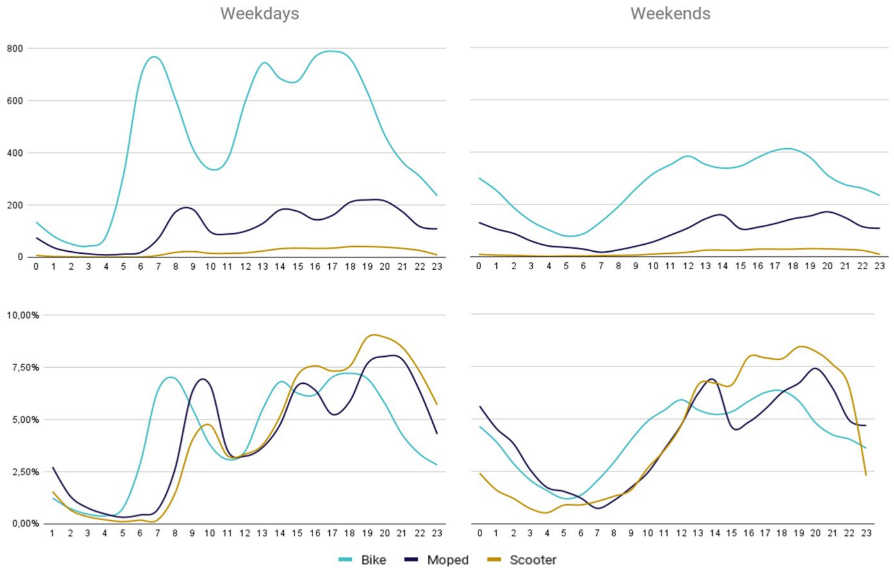

Fig. 3 Absolute (top) and percentual (bottom) distribution of departures by mode over an average day

activities as their prime time is when the week starts and especially in the PM rush hour when people usually are returning home, while the dockless services could be more related to other leisure/recreational activities, which supports what has been found in similar research (McKenzie 2019b; Ji et al. 2020). When analyzing the weekend behavior, we observe that for all the three modes, the highest departure counts are found on Saturdays and bikes and mopeds are preferred for an hour later (18 and 20 h, respectively) while scooters' preference is maintained at 19 h. Hence, we can infer that scooters' behavior is very similar disregarding the day of the week, while bikes and mopeds vary from weekdays to weekends. This is also noticeable when analyzing the coefficients of variation which describe how the services behave during the day, showing a more stable pattern for BiciMAD against a more unstable pattern shown for mopeds and scooters. Interestingly, the coefficient of variation in the three modes is lower for weekends, meaning that they behave with fewer variations along these days.

Figure 3 represents the absolute and percentual distribution of departures along the course of an average day. During weekdays, the three modes show three peaks associated with AM and PM rush hours and lunch or midday activities. However, some differences are noticed. The first one is that bikes are seen to be used in earlier hours (at 07, 13 and 17 h) compared to dockless services (at 09, 14–15 and 18–19 h). Secondly, bikes are used in the morning almost in the same way as they are used in the afternoon, which supports that the service has a more homogenous trip distribution about dockless services. Dockless services' departures increase toward the afternoon (especially scooters) showing a more unbalanced usage throughout the day. In the case of weekends, the AM rush hour peak disappears, and origins trips increase toward the afternoon in all modes, especially scooters and mopeds from 19 to 20 h. A new peak is seen though for all three modes in the early morning hours from 00 to 01 h, which is closely related to nightlife activities during weekends.

Figure 4 shows the daily behavior for departures (total count of origin points) by mode and according to the day of the week. The first noticeable difference is how each service's departures behave spatially. With bikes being a station-based model, they show a higher scale (ranging from cells that have from eight to 215 departures on an average day) which means a more intense usage of space as all origin points are aggregated only in those hexagons where bike stations fall at. On the contrary, dockless services allow users to start their trip at any location within the service's geo-fence, which causes a more dispersed usage of space as origin points are aggregated in more cells (ranging from one to 22 departures on an average day).

Moreover, the map yields the important differences between weekdays and weekends. During weekdays, trip departures cover a more extensive area, although none of them, except mopeds, extends beyond the M-30 highway urban area (central area of the city). When comparing both scenarios (weekdays and weekends), we see more trips starting from high employment areas of the city during weekdays (i.e., the north–south axe of Paseo la Castellana), as was also found in Forest (2019) and Lazarus et al. (2020). During weekends, however, these work-related activity areas are mostly turned off in terms of micromobility trip departures and they rather tend to be more concentrated around the city core center, especially, in the case of bikes. With most users not having to work or conduct routinary activities, weekends' behavior is more active at the city core center where most of the recreational/leisure/

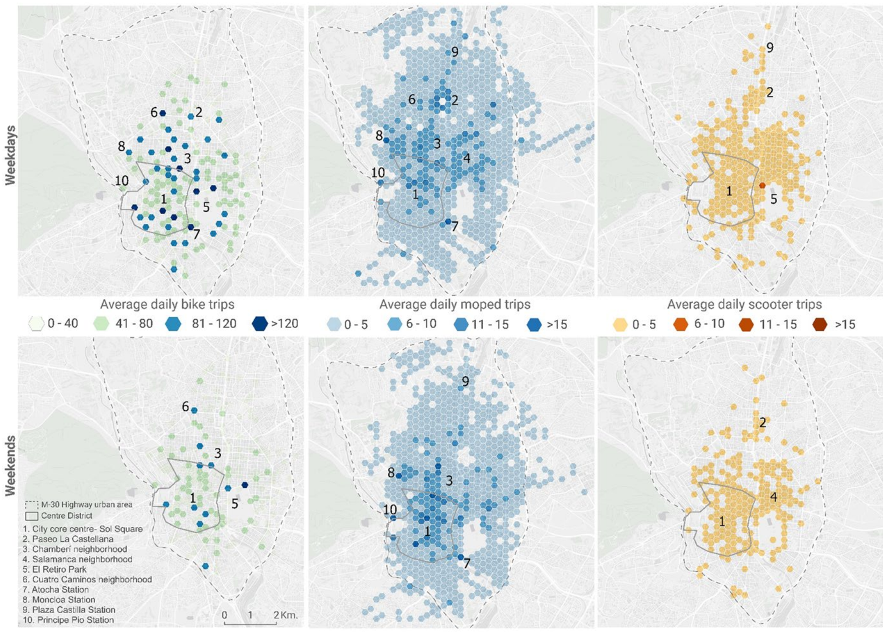

Fig. 4 Daily departures by mode and according to the day of the week

commercial areas are located as well as the most touristic and visited areas, also similar to findings in Yang et al. (2020) and McKenzie (2019a).

In general, departures for the three modes seem to be quite related to transport infrastructure and this relationship is maintained on both, weekdays, and weekends. Transport intermodal stations are very attractive and could be considered relevant infrastructures in terms of micromobility services, supporting findings from Duran-Rodas et al. (2019) and Teixeira and Lopes (2020). Central districts show to be important no matter the day of the week for both dockless services. These areas of the city concentrate on mixed-residential land use that hold a varied offer of activities throughout the day and throughout the whole week. While, in the case of bikes, a close relationship between the spatial distribution of departures with the location of cycling infrastructure (i.e., segregated cycling lanes) can be observed, supporting what was also found by Romanillos et al. (2018) and Talavera-García and Pérez-Campaña (2021).

4.2 Understanding spatiotemporal patterns

We take the advantage of STC constructs and visualize how departures distribute across space and along different hours of the day, which enables a better understanding of urban dynamics in a more granular manner (see Fig. 5). The results clearly

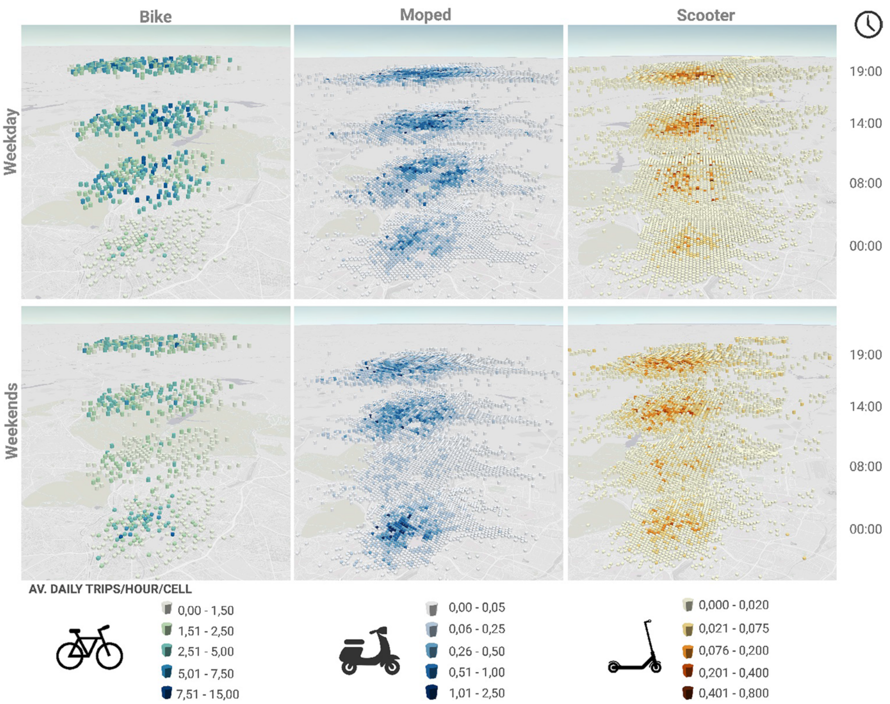

Fig. 5 Spatiotemporal distribution of micromobility departures on an average day

illustrate some important differences between weekdays and weekends dynamics. For all three modes, there are two main differences. The first one related to routinary activities (work/education or other) that take place during the morning rush hours, as at 08:00 h on weekends, trips drastically decrease (most people are free from routinary activities), while at this same time on weekdays, many trips are starting, and especially coming from residential zones. The second difference is related to nightlife activities that take place mostly during late night and early hours, as we can see the trips at 00:00 h considerable higher in weekends and mostly starting from locations at the city core center where most entertainment places are concentrated.

From space–time cubes, we can also infer that afternoon hour (from lunch on) are the most profitable ones for micromobility operators, as departures are maintained in high counts no matter the scenario (weekday or weekend) and they seem to be better distributed around the city urban area (greater coverage). In the case of weekdays, we can see the relevance that holds some of the most important office/workplace areas of Madrid where a high number of departures are observed around 14:00 h (lunch) and 19:00 h (return to home).

Hot and cold spot results support and emphasize the previous findings (see Fig. 6). There are few hotspots at 08:00 h on weekends and few hotspots at 00:00 h on weekdays. Additionally, from the hotspots results, we infer that afternoon hours are the most profitable time of the day, as they cover a greater surface in the city, disregarding the day of the week, even though they still tend to concentrate more on the city core center on weekends. These findings support what was also found in (Arias-Molinares et al. 2021). Therefore, hotspot

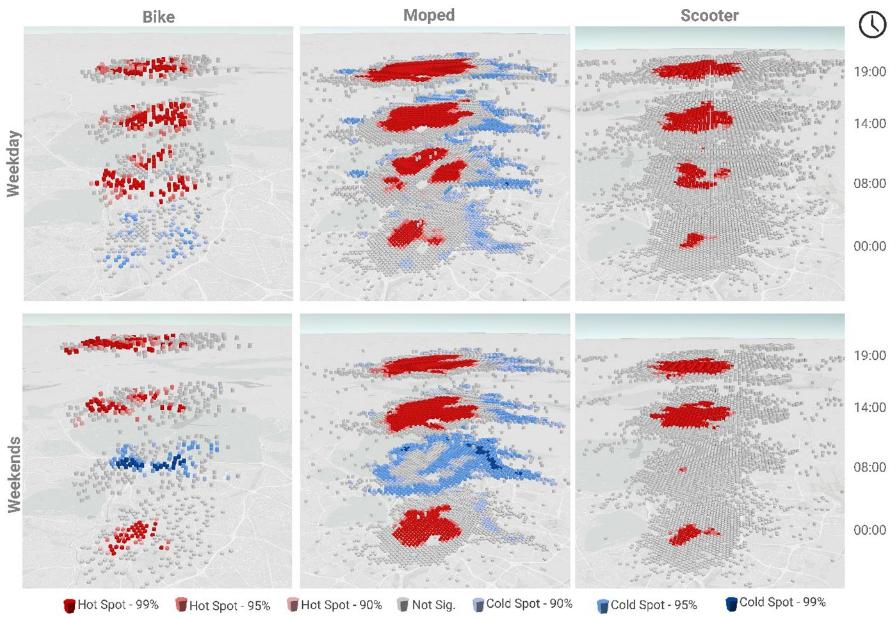

Fig. 6 Hot and cold spots results across time

areas represent the places of the city that have greater vitality and attractiveness in terms of micromobility departures, maintaining high counts throughout the day and not just specific hours which benefits operators as they do not need to redistribute as many vehicles. As we have seen, using STC visualization methods brings a new perspective to GPS data, as they complement what 2D maps are not able to capture, which is a more granular (hourly) analysis of differences/similarities.

Figure 7 shows the percentage of times that each location (hexagon) is a hotspot (with a *p*-value 0,05) which enables us to quickly identify the most important areas of the city regarding micromobility departures (origin points). The general pattern shows that trips start from a more extensive area during weekdays, covering those areas with a high concentration of workplaces/office sites. On the contrary, departures on weekends tend to be concentrated mainly around the city core center for all three modes. Mopeds represent the mode with the highest hotspot coverage area during weekdays and especially during weekends, which means its users are departing from many different locations of the city, while in the case of the other two modes (bikes and scooters), they tend to start their trips in more particular areas. Both maps allow the identification of the city core center and its surroundings as areas with more vitality in terms of micromobility departures during weekdays and weekends. This is related to the fact that these areas hold great employment and residential zones, a consolidated public transport and cycling infrastructure as well as a varied offer of commercial and recreational activities supporting findings (Yang et al. 2020).

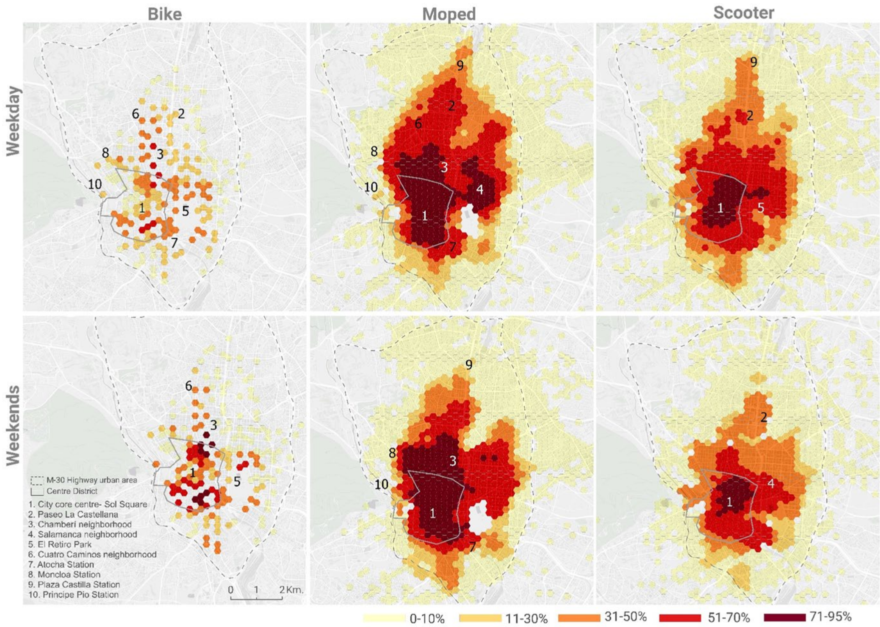

Fig. 7 Locations with the highest/lowest percentage of times being Hotspots (*p*-value 0,05)

4.3 Identifying locations with similar profile time

Once we understand the different daily/hourly dynamics, we can furtherly identify and group types of locations that share similar space–time behavior regarding micromobility departures. The results of the Time-Series Clustering analysis enable the identification of different clusters. Based on this method, and after different tests, our results show that the maximum dissimilarity between groups and maximum similarity within each group was obtained at five (5) clusters for each mode during weekdays and weekends (see Figs. 8, 9, 10).

The results obtained for the different clusters can be analyzed in terms of intensity (departure counts) and temporal variations. On one hand, regarding intensity, we observe differences for both, weekday and weekend scenarios, as the types Wd4/Wd5 and We4/We5 show a more intense usage ("intensity types" with higher departure counts) than the rest of the clusters. On the other hand, in terms of temporal variations, differences are more noticeable in the weekday scenario, as some types show high departure counts in both morning and afternoon hours (i.e., Wd4, Wd2 and Wd1), while others increase only toward the afternoon (i.e., Wd3 and Wd5). In the case of weekends, all the clusters increase in departures in the afternoon hours, being more similar in terms of temporal patterns and only differentiating themselves by usage intensity.

Moreover, the clusters' spatial distribution shows some important findings. One of them regard the different dynamics of weekdays and weekends and the other highlights the different land uses that are more active at certain hours. Regarding the first difference, during weekends, most high-intensity clusters are mainly concentrated

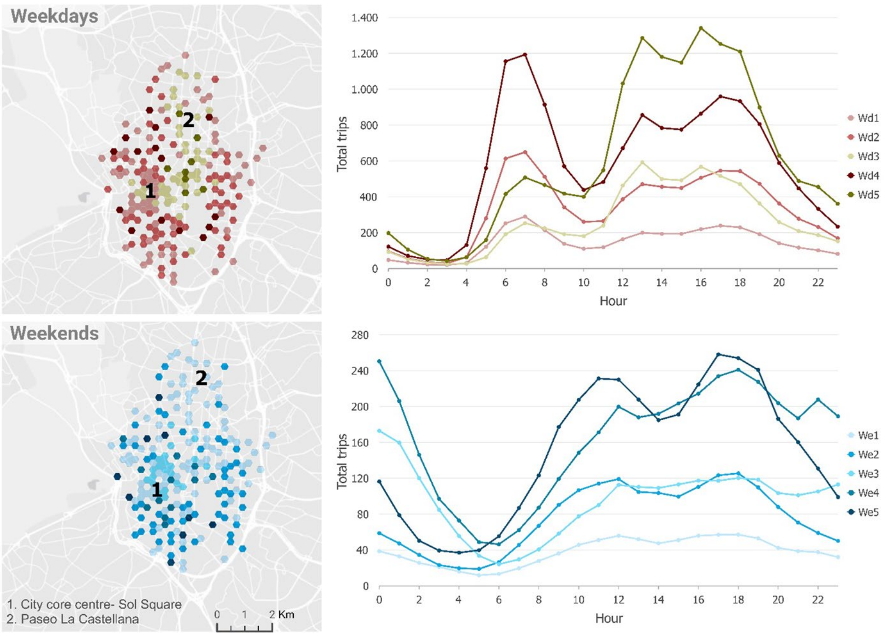

Fig. 8 Location clusters for bike departures

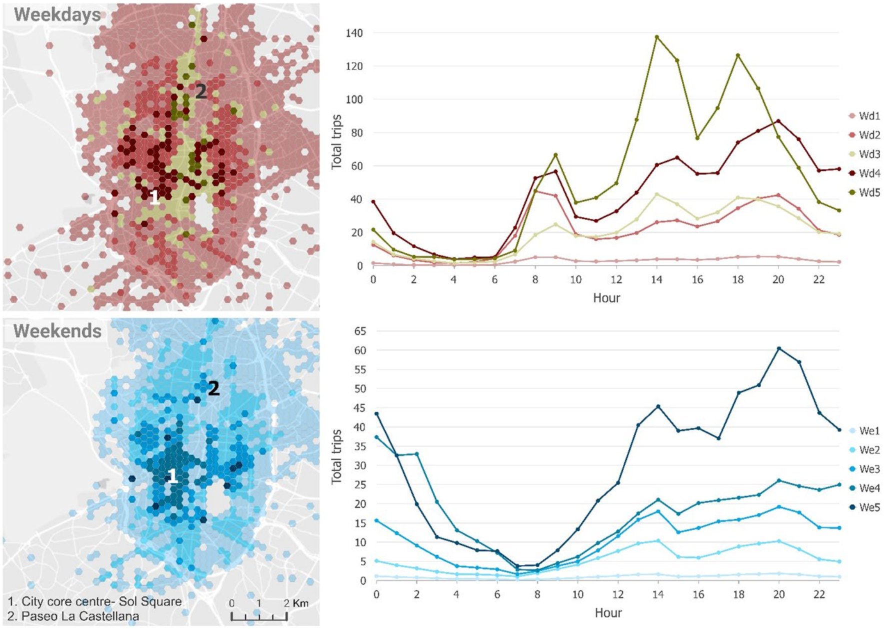

Fig. 9 Location clusters for moped departures

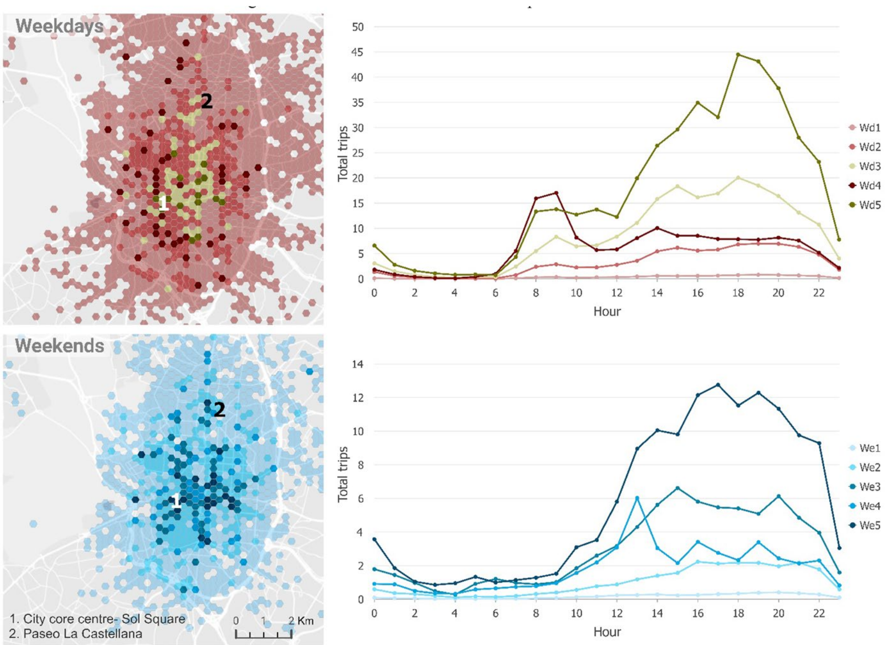

Fig. 10 Location clusters for scooter departures

around the city core center, except BiciMAD which seems to have a more homogeneously distributed pattern (in some cases related to transport intermodal stations). Regarding the second difference, the results show for all three modes, a consistent tendency for weekdays. During morning hours, areas with high usage (departures) intensity are mostly residential zones (types Wd1 and Wd2), while during the afternoon hours, the most active areas are workplace/office sites (Wd3 and Wd5). Those areas that have intense activity from both, morning and afternoon hours (Wd4), are the most profitable for micromobility operators. In these hours, the system is balancing itself with high vehicle rotation, while other areas, that have activity only during certain periods, require more vehicle redistribution.

As we have seen in previous figures, the different types of locations seem to be related to the dynamics associated with land use activity. Therefore, we try to explore this relationship in more detail by overlaying land use with the resulted clusters (Table 3). To respect the maximum manuscript length, we have only included the analysis of the weekday scenario. In general, for all three modes, we can observe that residential and mixed-residential land concentrate the highest percentages of clustered hexagons. Clusters Wd1 and Wd2 (low intensity and

Table 3 Distribution of location clusters (percent of hexagons) over land uses during weekdays

Mode	Land use	Wd1	Wd2	Wd3	Wd4	Wd5
Bike	Residential	36%	36%	12%	28%	23%
	Mixed-residential	46%	52%	71%	54%	59%
	Commercial	4%	2%	2%	0%	0%
	Workplaces (office)	3%	2%	9%	0%	9%
	Education	1%	1%	0%	0%	0%
	Parks	3%	2%	2%	8%	9%
	Other	7%	7%	4%	10%	0%
	Total	100%	100%	100%	100%	100%
Moped	Residential	55%	46%	21%	24%	14%
	Mixed-residential	28%	47%	63%	66%	61%
	Commercial	2%	1%	1%	3%	0%
	Workplaces (office)	7%	1%	7%	1%	22%
	Education	4%	1%	3%	1%	0%
	Parks	4%	2%	4%	2%	2%
	Other	1%	2%	1%	2%	0%
	Total	100%	100%	100%	100%	100%
Scooter	Residential	57%	29%	15%	31%	27%
	Mixed-residential	25%	57%	67%	57%	59%
	Commercial	2%	2%	4%	2%	5%
	Workplaces (office)	8%	3%	7%	2%	2%
	Education	4%	1%	0%	2%	0%
	Parks	4%	2%	5%	2%	7%
	Other	0%	5%	2%	3%	0%
	Total	100%	100%	100%	100%	100%

morning-afternoon peak) are mostly associated with departures from residential areas, with moderate usage intensity in departures for both, morning, and afternoon hours. Similarly, Wd3 (medium intensity), Wd4, and Wd5 (high intensity) are mainly located near mixed-residential land uses but show high usage intensity in departures for both morning and afternoon hours. Hence, we could infer that mixed-residential land use represents the most attractive areas for starting micromobility trips during the entire day.

On the other hand, some differences are noticed when considering other land uses. The highest percentage of hexagons associated with work activities is clustered Wd3 and Wd5 in the case of bikes, Wd5 for mopeds, and Wd1 and Wd3 for scooters, which are all clusters that share the characteristics of increased departures counts toward the afternoon. Consequently, bikes, mopeds, and scooters have a close relationship with departures in the afternoon from work-related areas (commute to return home). Moreover, educational land use is related mostly to clusters Wd1 for all modes, which is characterized by a low usage intensity but a clear morning peak period (probably related to the entrance to schools). Finally, parks are mostly associated with cluster Wd5 for bikes and scooters, and Wd1 and Wd3 for mopeds. Therefore, bikes and scooters show to be closely related to intense use of this mode for recreational purposes (especially in the afternoon hours), while mopeds are shown to have a more moderate usage related to this land use.

5 Conclusions

This study has shown that the exploration of spatiotemporal micromobility travel patterns can be better understood within the Time Geography framework, using space–time cubes. Micromobility systems generate huge amounts of data, in the form of trip GPS records, with high spatiotemporal resolution. This data facilitate the representation of spatiotemporal patterns in Space–Time Cubes (STC). One of the main findings is that bikes are the most important shared mode analyzed in the city as it shows high departure counts throughout the day while mopeds, and especially scooters gain importance toward the afternoon. In the case of Madrid, we have found that central (midday) and late afternoon hours (from 18 to 20 h) are the most profitable time for micromobility operators, as hotspots are more homogeneously distributed.

In addition, the analyses performed allowed us to identify the areas of the city with the highest vitality and attractiveness in terms of micromobility departures. These areas concentrate residential, mixed-residential, commercial, and work-related land uses that are closely linked to an intense usage during the entire day (morning and afternoon). Therefore, clusters Wd4/We4 and Wd5/We5 are the types of locations that represent the better scenario for micromobility operators, as redistribution trips could be reduced due to users starting their trips in the most attractive areas where others previously have left a vehicle as was also found in Arias-Molinares et al. (2021). This study identified five types of places according to each scenario (weekdays and weekends) and each mode, which offers valuable insights for micromobility operators to distribute their vehicles in the areas and at the specific times that increase profitability. During weekdays, the results show that there are some locations associated with high departure counts coming from residential (clusters Wd1 and Wd2) and commercial areas (Wd1), as well as the importance of certain modes to conduct certain activities (for example, mopeds in the afternoon and departing from work-related areas, as well as bike and scooter in the afternoon departing from parks). Nevertheless, micromobility seems to have a good capacity to serve trips associated with activities that Hägerstrand called flexible activities, such as leisure. Thus, the peaks are usually shown in the afternoon and evening hours, especially during the weekend. On these trips, micromobility is a good complement to public transport.

The proposed methodology could be implemented in any city and could offer operators and authorities useful insights regarding the hourly changing dynamics of shared services. Our aggregation approach was to add each origin point to the hexagonal grid (*XY*-axis) and bin (*z*-axis) that contained it, according to the specific location and time of the starting point, and then totalize (adding) all the origin points (departures) by hexagon over the day (daily) or hourly. This helped us to understand the spatial and temporal distribution of the origins of micromobility trips, identifying the most important areas and times of the day and their relationship with land uses. For policy-oriented decision processes, authorities should try to understand the different dynamics according to the day of the week and hourly patterns. Promoting dense, mixed-residential land use, and offering micromobility infrastructures such as segregated cycle lanes and parking places in hotspot areas could increase the importance and usage levels of these shared mobility modes.

As limitations of the study, we could highlight one related to the moped and scooter datasets used, which were provided by two and one, respectively, of the many operators in Madrid. Hence, it is important to consider that, while in the case of bikes with BiciMAD, we almost cover all records as there are few shared bike operators in Madrid, this is not the case for the other two modes. For dockless services, the results must be carefully interpreted, as we are not covering the entire available moped (27%) and scooter (15%) fleet, thus the presence of other companies would vary the vehicle density in some areas, which could have an impact that we are not yet able to identify. Future research could try to include more operators to analyze a better sample and conduct regression models to better explain the relationship between the types of locations (clusters) and the different land uses.

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