EXPLORING THE SPATIO-TEMPORAL DYNAMICS OF MOPED-STYLE SCOOTER SHARING SERVICES IN URBAN AREAS.

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RESUMEN

Spain is one of the countries with the highest shared mobility fleet in the world. The shared use of motorcycles, also known as moped-style scooter sharing, has spread far and wide throughout the country at a dramatic pace in recent years. Despite its increasing popularity and impact on urban mobility, efforts devoted to the study of its spatio-temporal travel patterns are still scant.

Based on the analysis of GPS records of an operator present in seven Spanish cities, this study aims to contribute to this research gap by analysing mopeds' location patterns over time and assessing how different dynamics influence its usage level and self-balance potential. Our study is replicable to different cities and different shared modes, since we propose a methodology to identify the most important origins and destinations over time and analyse the system's self-balance capacity based on spatial autocorrelation tools. These insights are useful for operators to adjust and optimise vehicle distribution routes and maintenance/recharge tasks, decreasing congestion and increasing efficiency. The results may also be helpful for policy makers when planning and offering effective policies and infrastructure to encourage shared mobility.

1. INTRODUCTION

In recent years, shared mobility has grown in many cities around the world. It has been defined as the short-term access to shared vehicles (cars, bicycles, moped-style scooters, and scooters), according to the user's needs and convenience, instead of requiring vehicle ownership (Shaheen et al., 2016). More specifically, the term micromobility was coined to refer to low-speed shared vehicles like bicycles and scooters (moped and kick-style) that have recently drawn more attention (Shaheen & Cohen, 2019). Micromobility offers a flexible transport option capable of avoiding road congestion, reducing the required parking space, lowering noise/air pollution, since all vehicles are hybrid-electric/electric, and last but not least, encouraging intermodality with mass transit. Additionally, mopeds particularly provide faster speeds than bicycles, and this is a very attractive mode for non-flat cities (Aguilera-García et al., 2020).

Studies regarding micromobility essentially focus on docked and dockless bike-sharing systems (for example, Gu et al., 2019; Ji et al., 2020; Lazarus et al., 2020), comparing bike-sharing to scooter-sharing services (McKenzie, 2019) or analysing scooter-sharing travel patterns (Feng et al., 2020; McKenzie, 2020), but there is almost nothing to be found related to moped-style scooter sharing particularly. Most contributions regarding mopeds are related to accidents and safety issues (Aare & von Holst, 2003; R. A. Blackman & Haworth, 2013; Haworth, 2012; Huang & Wong, 2015) or riders' attributes, but they only consider those *who own* a motorcycle (R. Blackman & Haworth, 2010; Jamson & Chorlton, 2009; Rose & Delbosc, 2016; Yannis et al., 2007). As a clean alternative to the car and as a growing shared mobility sector, we consider this effort to be worthwhile. The few studies that exist on shared mopeds focus on user characteristics and preferences (Degele et al.,2018; Aguilera-García et al., 2020).

Our study will focus not on users, but rather of their trips. Our objective is to analyse and visualise mopeds' urban footprint and compare its spatio-temporal dynamics in different cities. The research aims to fill a knowledge gap related to the spatio-temporal patterns of shared mopeds. It proposes an original methodology that uses spatial autocorrelation tools to analyse travel patterns and visualise spatio-temporal behaviour over time, identifying the spots where most trips begin or attend, and assessing to which extent the system is self-balanced, obtaining insights from different dynamics. We based our analysis on a dataset provided by an operator present all throughout Spain called Muving.

These kinds of data-sharing initiatives have grown increasingly popular in recent times and will continue to do so, especially with the institutional support that they are attracting; an example of this is the recent proposal to build the European Common Mobility Data Space (European Commission, 2020) as a strategy to enable data availability, access, and exchange between different stakeholders.

Our findings are useful for authorities to understand the mobility patterns of this important sector, plan and offer strategies or public policy, design infrastructure to promote their use, and regulate accordingly.

They are also important for shared mobility operators, adding value to raw datasets and using insights to improve everyday operational tasks (maintenance, recharging, and distribution of vehicles). The rest of the article is divided into four sections. Following the introduction, Section 2 summarises the related literature. Section 3 describes the study context, data, and methods used for the research. Results are presented in Section 4, and lastly, the main conclusions are outlined in Section 5.

2. RELATED LITERATURE

Urban mobility technologies have undergone substantial and increasingly rapid change over the past two decades, especially in relation to shared mobility services (Pangbourne et al., 2020; Shaheen & Cohen, 2018). The rapid development of social media, Information and Communication Technologies (ICT), and new business models based on the sharing economy have enabled these new services to appear in many cities, changing the transport supply and causing an important impact on travel behaviour. The European Commission has highlighted the importance of multimodality and new shared mobility solutions that take advantages from each mode and are proving crucial to improve the transport system's resilience (especially during the COVID-19 pandemic) (European Commission, 2020).

Some even consider shared mobility development as one of the three revolutions in urban transportation, along with vehicle electrification and automation (Fulton, 2018).

Shared mobility and micromobility are still relatively recent topics because the technology that allowed them to arise in many cities only occurred about a decade ago. Nevertheless, many studies related to bike-sharing (Eren & Uz, 2019; Ricci, 2015) have been published.

This was not the case for the scooter sharing sector (kick or moped-style), which is understandable, since it mostly started running operations only a few years back (in the case of Spanish cities, around 2017). Given the recent nature of their worldwide expansion, to our knowledge, only two studies have been found regarding moped-style scooter sharing. With the data provided by a German operator, Degele et al.,(2018) developed a cluster analysis to segment users according to their age, time between rides, distance driven, and revenue per customer.

They identified four types of moped users (power users, generation-X casual users, generation-Y casual users, and one-time users), analysed which type provided the most revenue, and proposed strategies to retain and promote their usage.

On the other hand, (Aguilera-García et al., 2020) conducted a generalised ordered logit model to identify the key drivers determining the adoption and frequency of use of mopeds in Spanish urban areas. They found that both personal socioeconomic characteristics and trip-related attributes played a major role in explaining the adoption of scooter-sharing services. Young and highly-educated people proved to be the segment of the population with the highest probability of using mopeds, but they also found a considerable amount of people in middle-aged groups.

None of the previously mentioned studies examined the spatial distribution patterns of moped trips. However, bikeshare-related studies can offer some lessons on travel behaviour associated with these systems. Temporal usage patterns show a morning and an evening peak, especially for commuting (Wang et al., 2018). Spatial analyses show that bikes are commonly taken from residential areas to travel to commercial zones, central business districts (CBDs), employment centres, and train stations in the morning, and back to residential areas during evenings (Caspi et al., 2020). In addition, it has been found that the temporal and spatial concentrations of dockless bikes are mainly influenced by the built environment, particularly density and street connectivity (Xu et al., 2019), and that most riders cycle short distances in urban centres (Li et al., 2018). Bicycle travel times are especially competitive compared to other transport modes for short trips in the city centre during peak periods (Romanillos & Gutiérrez, 2019). Most of these papers used GPS datasets collected by operators.

Studies regarding micromobility and the analysis of spatial patterns using spatial autocorrelation tools are particularly scarce. An exception is the study on shared e-scooters by Jiao & Bai (2020) which uses univariate LISA to identify areas of high demand (hot spots) as a preliminary step before applying regression models. We elaborate on this research line and use the most common spatial autocorrelation tools to explore micromobility trips, making use of univariate and bivariate Global Moran's I and LISA statistics and including the temporal component (time bands) in order to capture the dynamics of the system. Univariate analysis allows us to answer the questions of when and where demand is more clustered, and bivariate analysis allows us to answer the question of when and where demand is more self-balanced. Both issues (demand concentration and self-balance potential) are key elements for good management and planning of micromobility services.

3. STUDY CONTEXT, DATA, AND METHODOLOGY

3.1 Study context

Spanish city centres are generally characterised by old historic urban structures, with narrow streets and recurrent congestion problems, which could positively influence the use of shared mopeds. Whatever the reason, the country is one of the hubs with the highest shared moped fleet in Europe, resulting in approximately 9,000 motorcycles (Aguilera-

García et al., 2020; Howe, 2018). This research was conducted with a dataset provided by one of the most important operators present in seven Spanish cities in 2019: Madrid, Valencia, Seville, Saragossa, Malaga, Cordova, and Cadiz. Table 1 summarises some of their relevant characteristics for the study. As can be seen, Madrid and Valencia are the most important cities in terms of population; however Saragossa, Seville, and Cadiz also show high density (Inh/km^2) which is an important factor influencing the adoption of shared services (Munkácsy, 2017; Velázquez Romera, 2019).

Three of them are coastal cities, which usually have higher tourist activities promoting the use of mopeds. Warmer cities are mostly within the Andalusia Region in the south of Spain (Seville, Malaga, and Cadiz). Annual precipitation level is low in the seven cities analysed, which is also important to consider, as rainfall may reduce the use of micromobility in general.

Attribute		Madrid	Valencia	Seville	Saragossa	Malaga	Cordova	Cadiz
Population (municipality)		3,174,000	791,413	688,711	666,880	571,026	325,701	116,027
Average annual temperature (ºC)		15.0	18.3	19.2	15.5	18.5	18.2	18.6
Average annual precipitation (mm)		421	475	539	322	534	605	523
Coastal city		No	Yes	No	No	Yes	No	Yes
Modal split (%)	Public transport	24	21.8	26.2	24	13.2	12.04	7
	Car	39	21.5	35	28	37	44.15	48
	Active**	37	56.7	38.8	48	49.8	43.81	45
Moped-style scooter-sharing operators	Number of operators	4	3	2	2	1	1	1
	Name of companies	Acciona, Movo, Ecooltra, Muving	Acciona, Ecooltra, Muving	Acciona, Muving	Acciona, Muving	Muving	Muving	Muving
Topography		Hilly	Flat	Flat	Flat	Flat	Flat	Flat

Table 1 -Summarised characteristics of the seven cities analysed. Source: the authors with data from Greenpeace, (2019). *updated with results from the last Mobility Survey in 2018 (Comunidad de Madrid, 2018). ** Active = walk + bicycle + other low-speed mode. Data for Cordova and Cadiz was extracted from official reports (ETRALUX, 2011; Junta de Andalucía, 2018).

Only Valencia and Madrid have three or more moped-style scooter sharing operators. In the case of Madrid alone, some studies point to its role as one of the most important shared mobility labs in Europe, with an estimated fleet of more than 20 thousand vehicles (Arias-Molinares & García-Palomares, 2020a; Granda & Sobrino, 2019). These operators usually manage and maintain a fleet offered through an application where individuals access and subscribe to their service. Users pay a fee every time they use a vehicle, while operators are in charge of energy consumption and maintenance. In Spain, electric vehicles do not have parking restrictions in city centres and generally benefit from free on-street parking, providing an attractive alternative for inner districts (for example, in the case of Madrid, within the M-30 highway) (Aguilera-García et al., 2020).

3.2 Data

The dataset for the study contains data collected by the GPS devices installed on mopeds owned by Muving. The data was provided in CVS format, including all trips made between 13 February 2019 and 31 December 2019, and the following information:

- *Id_vehicle:* an identification number for each motorcycle.
- *Id_customer:* an identification number for each user.
- *Start_time:* trip starting timestamp (format: yy-mm-dd hh:mm:ss).
- *Start_latitude and longitude:* xy coordinates where the motorcycle was picked up.
- *End_time:* trip ending timestamp (format: yy-mm-dd hh:mm:ss)
- *End_latitude and longitude:* xy coordinates where the motorcycle was left.
- *Trip time:* trip duration in minutes.
- *Travelled distance:* travelled distance in km of the real trajectory by the street network.

3.3 Methodology

The data workflow covered entering, cleaning, transforming, describing, analysing, and visualising data. Given the size of the dataset (almost two million entries), we processed it using Python (vs 3.8) programming language. A script performing all steps was created: to load the CSV files, extract the day and hour of the trip in the timestamp information, and obtain a new output table. This output table was then imported to a GIS environment (ArcGIS Pro vs. 2.5.2) to display coordinates, geolocate points, and create a new column with the city name. An outlier cleaning process followed, using travelled distances, which in some cases went unrealistically higher than average. In order to discard these outliers, boxplots were made for each city and the final valid dataset included 1,797,2228 trips (see Table 2).

City	Trips with outliers	Distance (km) from which outliers were identified (boxplot)	Trips without outliers
Madrid	307,876	9.3	298,031
Valencia	437,795	8.1	425,683
Seville	477,424	8.4	463,825
Saragossa	201,294	8.6	195,942
Malaga	135,626	9.8	131,940
Cordova	126,061	6.4	121,034
Cadiz	163,616	6.7	160,773
Total	**1,849,692**		**1,797,228**

Table 2 -Dataset without outliers. Source: the authors.

Since time and distance travelled were provided, we calculated average speed, as well as some other indicators, like average usage (trips/customers) and average vehicle rotation per day (trips/vehicles/365days per year). Consequently, a model builder was created in ArcGIS to split the dataset by city, day of the week, and time band. We decided to aggregate the days of the week into two groups: working days (from Monday through Thursday) and weekends (Saturday and Sunday).

We excluded Friday from working days because in Spain, as described by Romanillos (2018), it is common to finish work earlier on Fridays, with particular travel patterns that could influence the normal working-day dynamic.

Regarding time bands, we selected four different hour periods: from 07 to 10 to evaluate the morning peak, especially for obligatory trips (commuting to work/study), 13 to 16 to analyse midday behaviour (lunchtime or midday activities), then 19 to 22 for after-work activities and/or return-to-home trips, and finally, from 23 to 02 hours to evaluate nightlife patterns. After splitting the dataset by time bands, the different layers according to each scenario (city, day of the week, and time band) were spatially aggregated into a hexagonal grid, obtaining the number of starting/ending trips by hexagon. Studies focusing specifically on walking distances to pick up shared mopeds were not found, but (Aguilera-García et al., 2020) found that users were willing to walk up to 500m. Hence, we determined 200 meter-sided hexagons with a surface area of 10,3923048 Has as the optimal size to aggregate our data, since 200m appears to be an acceptable walking distance to pick up a motorcycle.

Lastly, the hexagonal grids were used to perform location patterns analysis using ESDA tools. To this end, we used GeoDa software (vs 1.16.0.16) to calculate two different Global Moran's Indices (Anselin, 1995). The first one was univariate Global Moran's I statistics for origins and destinations separately. This helped us to study the level of concentration or dispersion of the origins and destinations of moped trips, and their variation over the course of the day. This insight could be of interest to inform operators as to the most optimal time and location to carry out operational tasks, like vehicle redistribution, recharging, and maintenance, and to know when/where demand is coming from. In addition, bivariate Global Moran's

I was calculated to measure the spatial association between the destinations and origins of trips. Insights from this statistic served to analyse whether the system is self-balanced throughout the day by answering the question: "*are users ending their trips near where others are starting theirs?*" If the system is balancing itself, then the locations where users are arriving at a certain time are also the locations where other users are starting their trips, allowing for higher vehicle rotation. Both univariate and bivariate Global Moran's I statistics were calculated using a contiguity weight matrix of 1st order. The resulting univariate and bivariate Global Moran Indices and their z-score were graphed, and symbology was applied to the hexagonal grids, generating maps by time bands.

Figure 1 illustrates the conceptual framework of the different Global Moran's Indices calculated, in relation to expected origin-destination location patterns. Our hypothesis predicts that origins are more dispersed than destinations in the early morning band (predominance of trips from residential areas to the city centre), while the opposite should occur in the last bands of the day (predominance of return-to-home trips).

It also expected that the system will tend to balance itself during the middle bands, since, at those hours, the population tends to be concentrated in the city centre, which produces a greater proximity between origins and destinations.

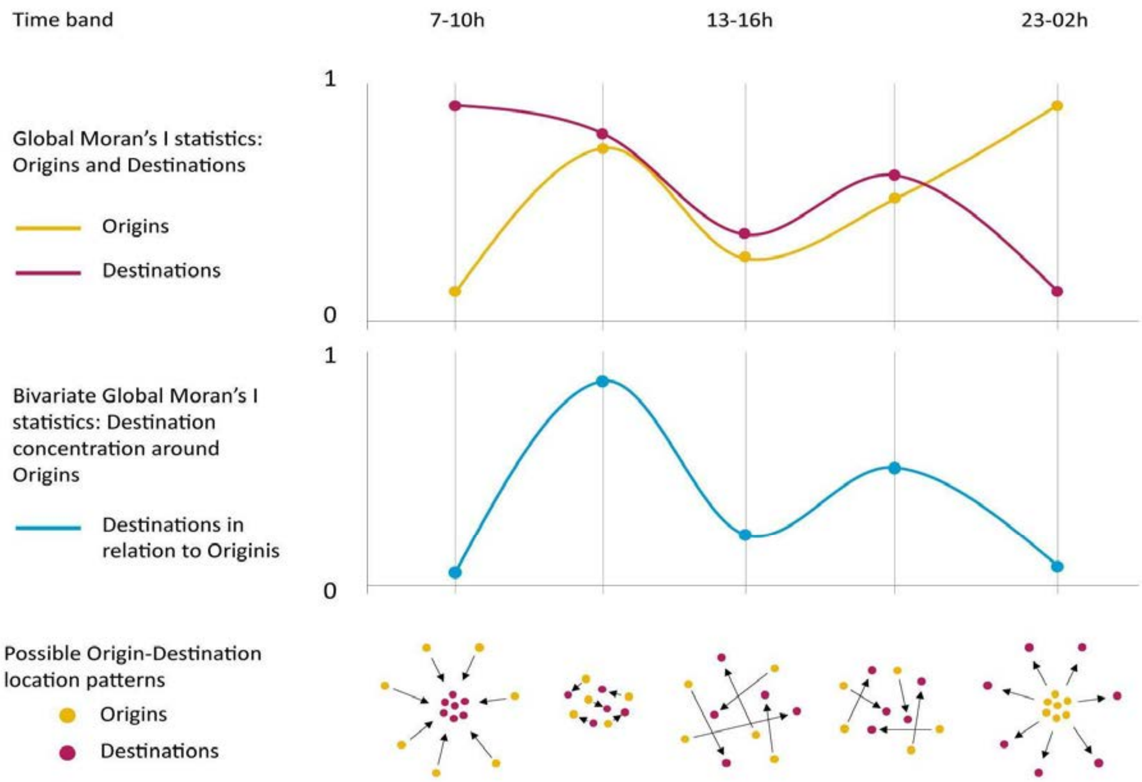

Fig 1- Conceptual framework of the different Global Moran's Indices calculated. Source: the authors.

In addition, univariate Anselin Local Moran's I (LISA statistic) was used in order to identify and map local tendencies (clusters and outliers) related to the location of origins and destinations by time bands. With LISA statistics, it is possible to distinguish High-High clusters (a high value surrounded primarily by high values), Low-Low clusters (a low value surrounded primarily by low values), and spatial outliers, either High-Low (high values surrounded primarily by low values) or Low-High (low values surrounded primarily by high values) (Anselin, 1995). Lastly, bivariate LISA cluster maps for origins and destinations, by time bands, and on working days, were graphed in order to identify areas with a high concentration of both origins and destinations (HH clusters) in which the system self-balances, or other areas with imbalances between origins and destinations (HL and LH outliers).

4. RESULTS

4.1 Service characteristics and performance

Table 3 shows the descriptive characteristics of the dataset analysed. Seville and Valencia generated the greatest number of trips during 2019, with 463,825 and 425,683 trips respectively, while Madrid, the most populated city, generated 298,031.

In relation to this fact, it is important to consider that large metropolitan areas usually have more operators, so competition is a crucial factor that determines their market share. In addition, Madrid is one of the cities with the highest shared mobility fleet, not only of mopeds, but also of other modes like bicycles, cars, kick-scooters, etc.

This context could also explain why, although Madrid has more deployed vehicles, Valencia and Seville show a higher number of trips and more trips per customer throughout the year, with 13.87 and 12.92 respectively, in comparison with Madrid, with 9.33 trips per customer. The average vehicle rotation per day results in 2.04. Cities above this average, like Cadiz, Saragossa, Seville, and Valencia, are more attractive for companies (as the system is more profitable) than, for instance, Madrid, which bears the minimum value with just 1.08 vehicle rotations per day.

City	**Trips**	**Vehicles**	**Customers**	**Usage** (trips by customers)	**Veh. rotation/day** (trips/vehicles/365 days)	**Average trip time** (min)	**Average trip distance** (km)	**Average Speed** (km/hr)
Madrid	298,031	755	31,934	9.33	1.08	11.48	3.49	18.24
Valencia	425,683	578	30,692	13.87	2.02	10.28	3.18	18.56
Seville	463,825	591	35,902	12.92	2.15	10.40	3.23	18.63
Saragossa	195,942	240	15,313	12.80	2.24	10.53	3.42	19.49
Malaga	131,940	196	12,613	10.46	1.84	10.86	3.68	20.33
Cordova	121,034	184	9,715	12.46	1.80	9.06	2.67	17.68
Cadiz	160,773	186	10,755	14.95	2.37	9.05	2.73	18.1
Total	**1,797,228**	**2,414** (316 vehicles duplicated in different cities)	**129,384** (17,540 users duplicated in different cities)	**13.89**	**2.04**	**10.24**	**3.20**	**18.72**

Table 3 -Descriptive characteristics of the dataset analysed. Source: the authors.

Average trip time, distance, and speed prove relatively homogenous across the different cities, with a trip time of around 10 minutes, a 3 km distance, and an 18km/hr speed. The city with the highest trip time is Madrid (11.48 minutes), which could be expected since it is the capital of Spain and is a more congested urban area.

However, this 12-minute ride is still relatively fast compared to other services, such as bike-sharing, which displays trip times of 15 minutes or more (Romanillos, 2018). In any case, travel time and distance may be highly influenced by the size of the company’s service area. Certainly, future expansions of these areas could allow users to travel longer distances. Regarding distances travelled, mopeds are mostly used for short urban trips between 1 and 3 km (see Figure 2). Madrid, Valencia and Seville, which are large metropolitan areas, display a considerable number of trips with longer distances.

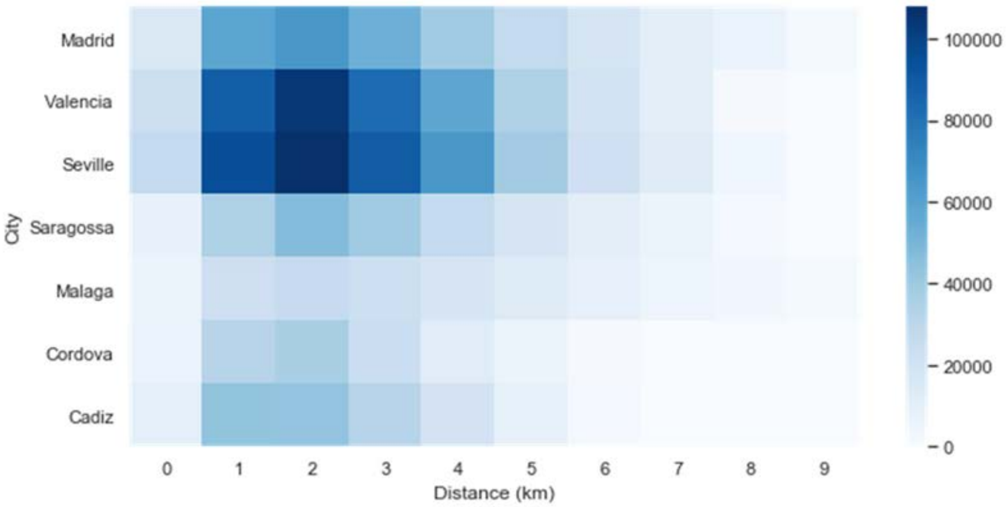

Fig 2 - Number of trips by distance travelled and city. Source: the authors.

In addition to this comparative analysis between cities, when it comes to general fleet and customers, we found that 2,414 mopeds were operating in Spain during 2019 and almost 130,000 clients used one (of which 17,540 made trips in more than one city). The fact that some customers use the app in different cities could demonstrate their intention to use this kind of platform when travelling to different areas, which is an important insight, especially with the introduction of new concepts like Mobility as a Service (MaaS) (Arias-Molinares & García-Palomares, 2020b; Jittrapirom et al., 2017).

4.2 Temporal patterns

When analysing average daily trips by month, we identify a general trend for Spanish cities, with high peaks in March, May and October, and valleys in April and August (see Figure 3). Peaks are related to the beginning of spring season, when the temperatures rise and shared mobility becomes more attractive. High trip counts in September and October correspond to the return from summer holidays when users begin their daily routines again.

The valley seasons (April and August) concentrate most holidays (especially the summer season), when most Spaniards travel for holiday; this is very notorious in the case of Madrid, where the trip count drops considerably. Cities that follow a different trend are, for example Seville, which shows a high peak in April. This is probably due to the increase in tourist and local activity during the Holy Week and Seville’s Fair.

Other cities that follow different patterns are Malaga and Cadiz, which display high number in August, possibly related to the fact that these cities are summer tourist destinations. In these latter cities, trip counts are homogenous throughout the year, increasing notoriously only during the summer season, from which we might infer that many of the moped users during those months are tourists.

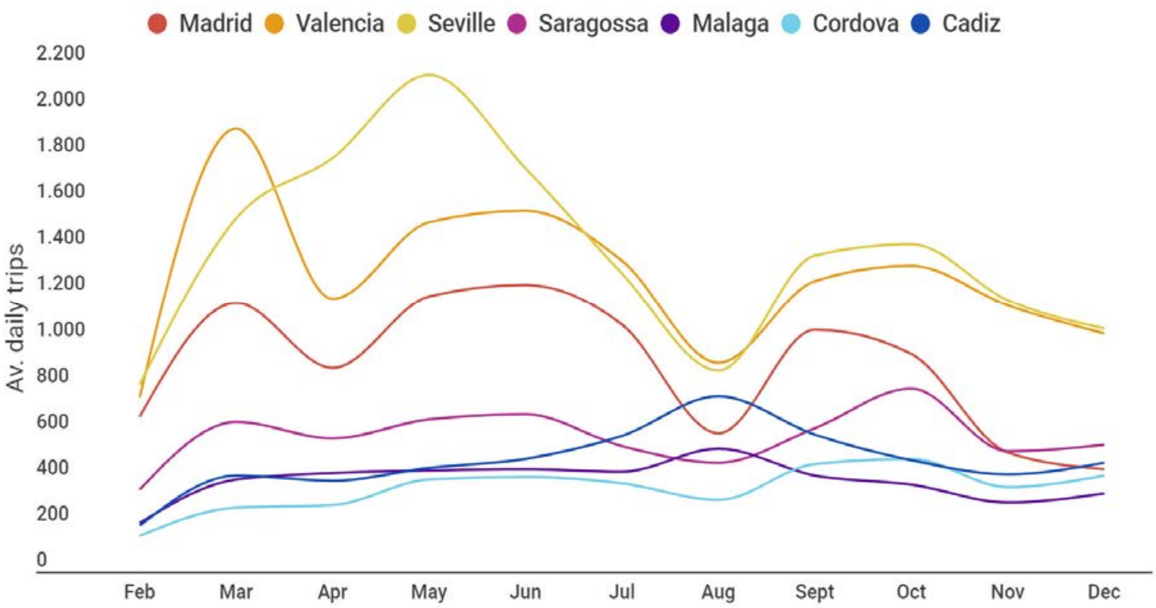

Fig 3 - Average daily trips by month (2019). Source: the authors.

When aggregating data by day of the week, Table 4 shows that in general, 72% of the trips are made on working days and 28% over weekends. These results lead us to infer that mopeds are not only used for recreational trips, but also for other purposes, like commuting or running errands. Figure 4 shows that the distribution of trips is quite homogeneous throughout the week in greater detail.

City	Working days (M-T)	Friday	Weekends (S +D)	Total
Madrid	169,425	45,773	82,833	298,031
Valencia	240,681	62,587	122,415	425,683
Seville	262,801	71,843	129,181	463,825
Saragossa	107,846	29,684	58,412	195,942
Malaga	73,771	20,030	38,139	131,940
Cordova	67,629	18,869	34,536	121,034
Cadiz	90,363	24,037	46,373	160,773
Total	**1,012,516**	**272,823**	**511,889**	**1,797,228**

Table 4 -Trips by day of the week. Source: the authors.

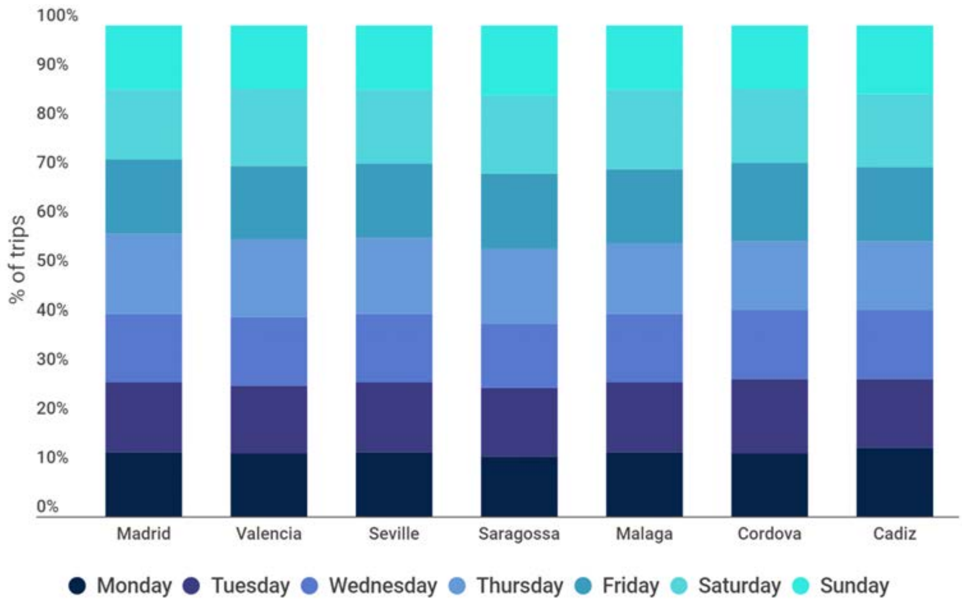

Fig 4 -Percentage of trips by day of the week. Source: the authors.

When exploring hourly patterns, Figure 5 shows the average daily trips on working days and weekends. Relatively homogeneous temporal behaviour is revealed with trips increasing toward the afternoon. We noticed three different peaks: the smallest one from 8 to 9 for commuting, a medium one from 13 to 14 related to midday activities (i.e., lunchtime), and the greatest one from 18 to 20 related to after-work activities and/or returning home. On the other hand, over weekends, the early morning rush hour disappears, and the midday peak (13-14 hrs) becomes as great as the night-time period (19-20 hrs), since many people start doing their activities from late morning onward. And lastly, over weekends, a significant percentage of trips is observed in the early hours (dawn), when customers use mopeds to return home from their night-life activities, given that the subways or public transport options are more limited. Given the lower usage over the weekend and the greater diversity in purpose, the spatial analysis was performed only for working days.

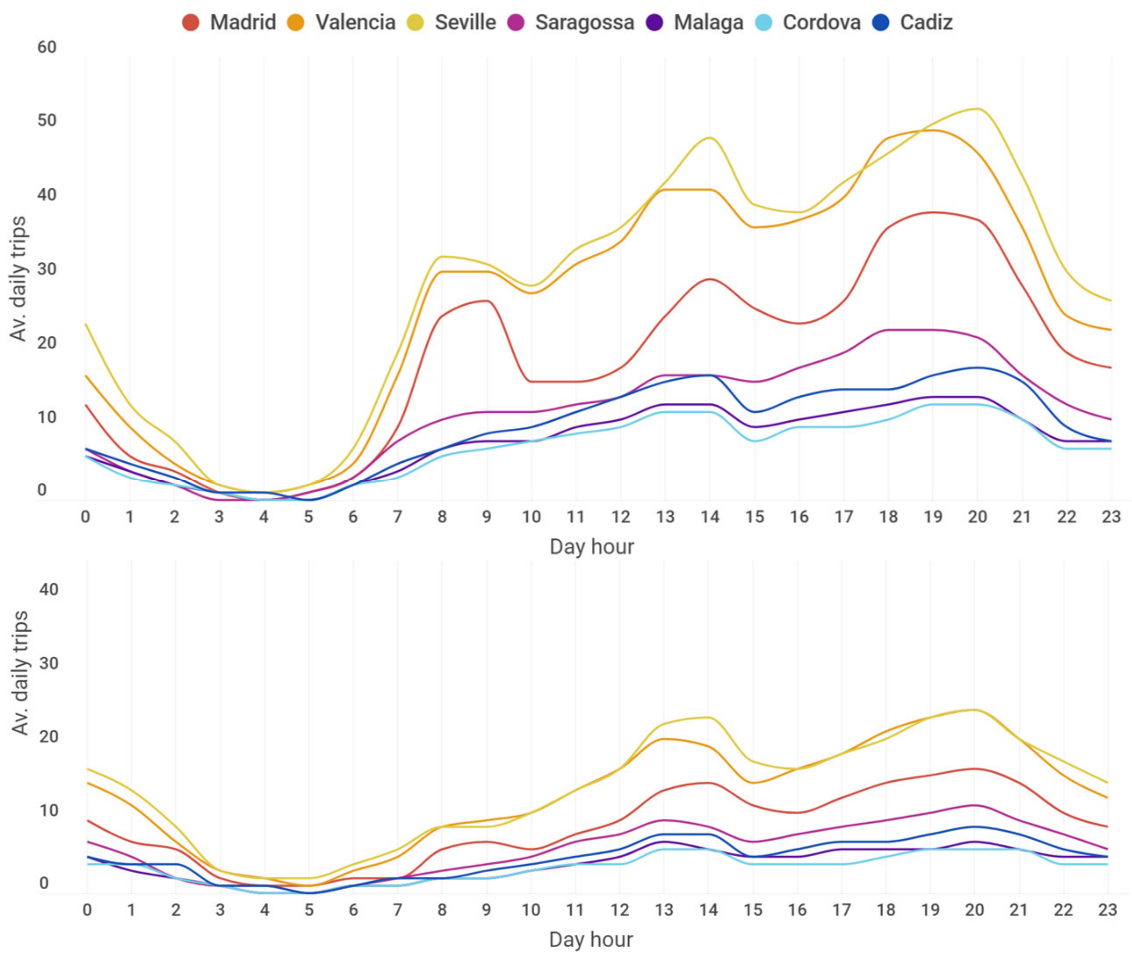

Fig 5- Average daily trips by hour of the day (top: working days, bottom: weekends).
Source: the authors.

4.3 Mapping origins and destinations of trips over time

Visualisation of the spatial distribution of trip origins and destinations over the course of a working day is shown in Figure 6. In general terms, it reveals that, in the first band (07-10), origins are more dispersed than destinations, while in the last time band (23-02), the opposite occurs. This pattern follows the hypothesis outlined in the initial conceptual framework, as morning users usually come from different residential zones and commute to (mostly) specific clustered workplaces. In the late hours, users do the opposite, coming from clustered after-work locations and returning to those dispersed residences. In some cases, these residential areas may match, meaning that late-night users are leaving mopeds at the same or near the same areas where morning users will take them, which will make the system self-balanced. However, in most cases, the ending spots do not match the starting ones, which requires vehicle redistribution by the operator to cover demand areas in mornings.

On the other hand, band 2 (13-16) and 3 (19-22) have more similar dynamics since origins and destinations are homogeneously distributed, with a slight difference in band 3 when destinations appear to be a bit more concentrated. In these two bands, trips are coming and arriving at similar areas, enabling a higher vehicle rotation. This time period of the day responds to midday-activities, like having lunch, running errands, and doing after-work activities, which usually take place at public facilities, restaurants, bars, gyms, and entertainment locations that are very spread throughout the city. This contributes to a less marked difference between origins and destinations. Hence, this is the period of time when the system's self-balance potential is most realized, in comparison with bands 1 and 4.

These results illustrate that the different spatio-temporal dynamics for shared mopeds in cities are closely related to their land-use distribution. For each city, we can identify the most important origins and destinations by time of the day, which informs operators where to allocate their resources at each time to cover a greater demand, and also for public authorities to know where to allocate infrastructure like parking facilities. The results obtained in the particular case of Cadiz, for this analysis and subsequent analyses, must be carefully interpreted, considering its particular location and shape: the city of Cadiz is located on a narrow slice of land surrounded by the sea. All results and maps are affected by this spatial singularity.

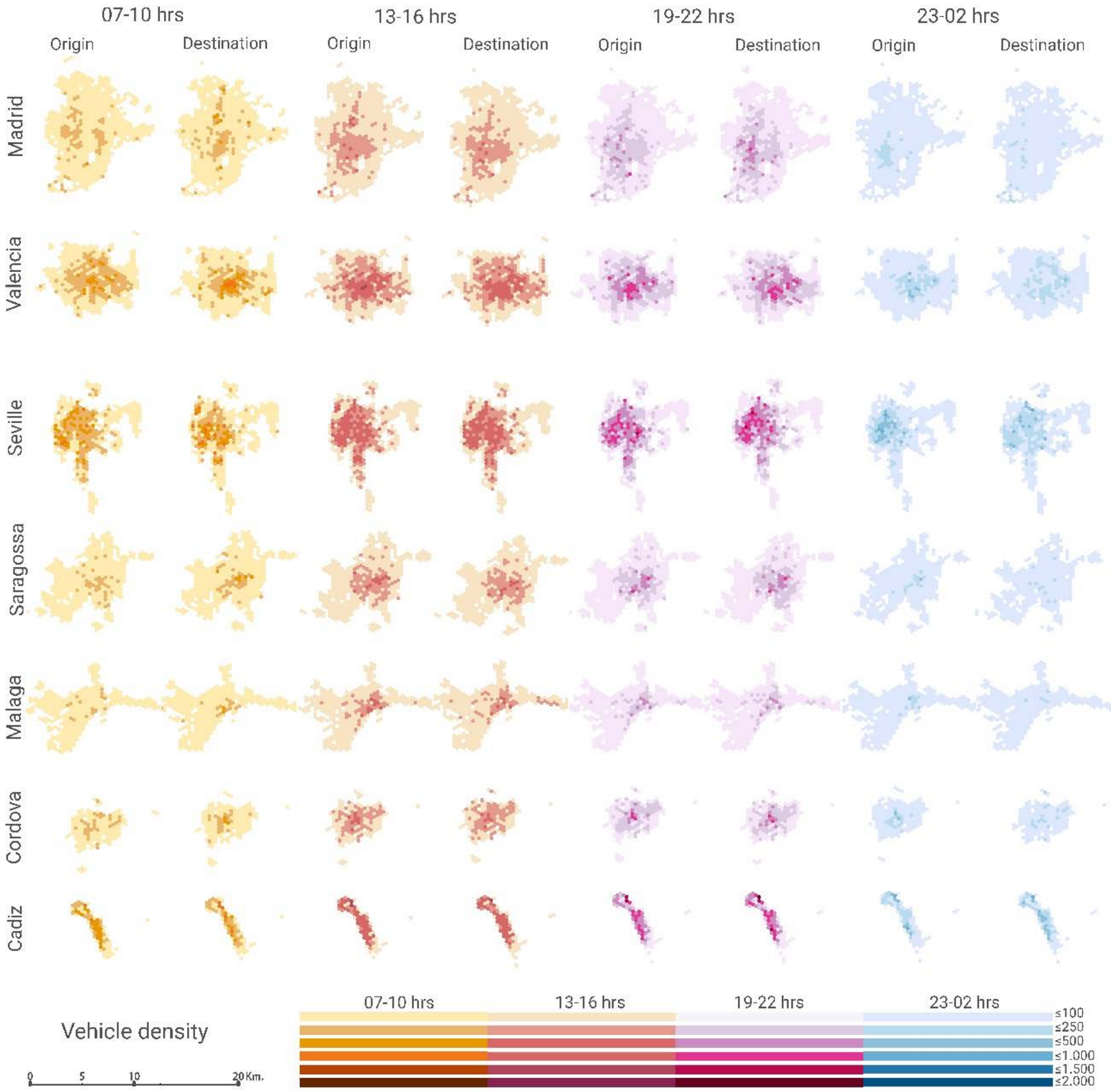

Fig 6- Spatio-temporal dynamics of mopeds during working days. Source: the authors.

4.4 Spatial autocorrelation analysis: local trends

As described in the methods section, in addition to map visualisations, we performed a series of spatial statistical analyses in order to further explore and quantify the trends previously identified. Firstly, Anselin Local Moran's I statistic was calculated in order to map the presence of origin and destination clusters at local level. The maps illustrated in Figure 7 show the marked differences between High-High clusters in bands 1 and 4, due to the location of residential zones and workplaces, especially in Valencia and Madrid, whereas HH clusters in bands 2 and 3 are located quite similarly. In all cases, there is a clear concentration of HH clusters in the city centre and LL on the periphery. Interestingly, the HH cluster maps of destinations in each time band are very similar to the HH cluster maps of origins in the following time band, which proves that the availability of vehicles near the users' location clearly influences increased usage.

Moreover, interesting results are obtained from observing spatial outliers, especially in the first band, which is mostly for commuting trips. In Madrid, for example, an HL spatial outlier for origins is located at Ciudad Universitaria, which is Madrid's main higher-education hub, meaning that from 07 to 10 AM, many trips begin on these university campuses.

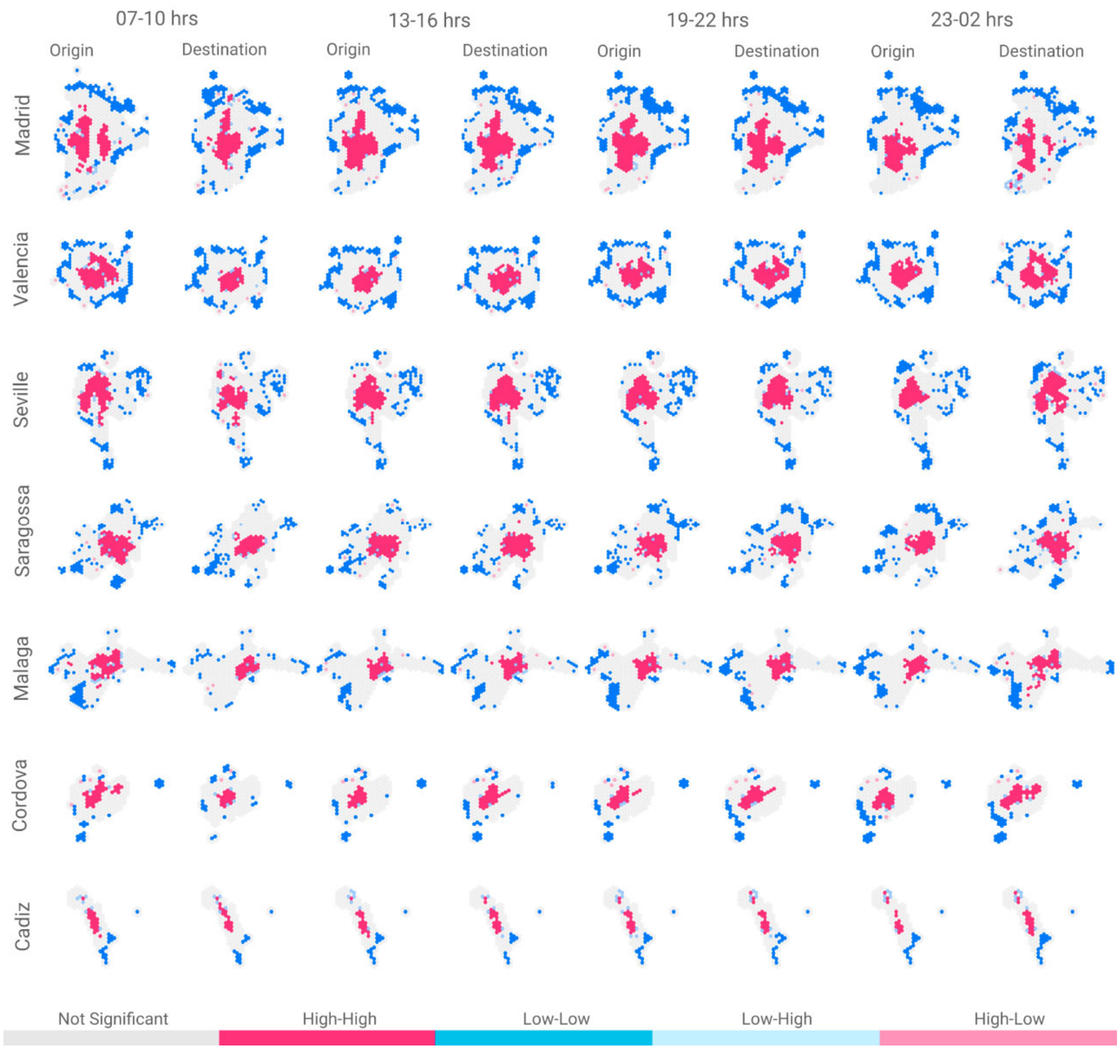

Fig 7- Univariate LISA cluster maps for origins and destinations by time bands and working days. Source: the authors.

When considering Madrid as an example case to zoom closer, we differentiate certain dynamics throughout the day, especially during band 1 (see Figure 8). In the morning hours, demand mostly comes from districts that concentrate residential zones with a medium-high income population (Chamberi, Salamanca, and the east area of Tetuan) and mostly arrives at workplaces and offices located over the north-south axis of Paseo de la Castellana. The geolocation of demand is consistent with results obtained by Aguilera-García et al. (2020), which revealed that most moped users had relatively high incomes.

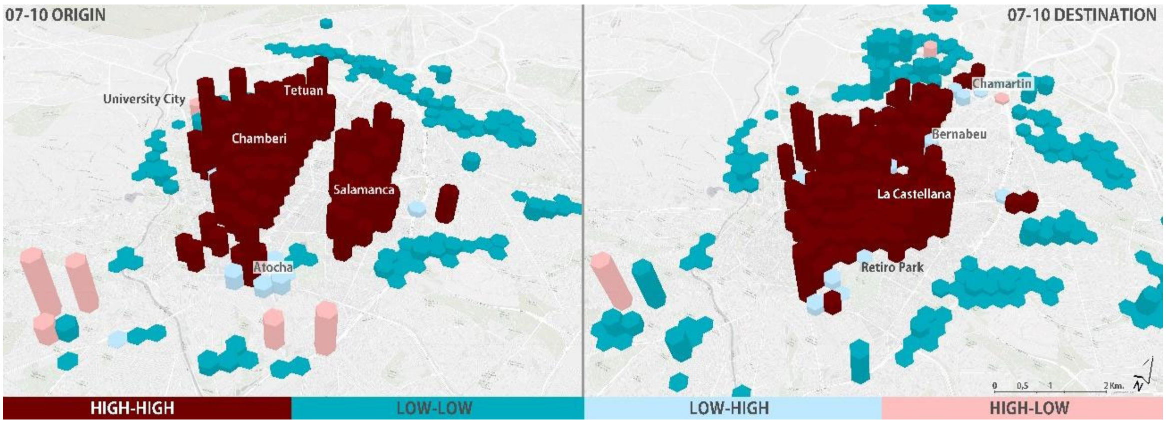

Fig 8-visualisation of Madrid's spatial clusters on band 1 during working days. Source: the authors.

Moreover, Bivariate Anselin Local Moran's I statistics for destinations around origins were calculated for every city and time band on working days. The results illustrated in Figure 9 show the same centre-periphery pattern for all case studies, with the exception of Cadiz, which seems to rather have a north-south pattern with HH clusters in the north area and LL clusters in the south. We observe that in time bands 2 and 3, HH clusters are more compacted around the city centres in comparison with bands 1 and 4.

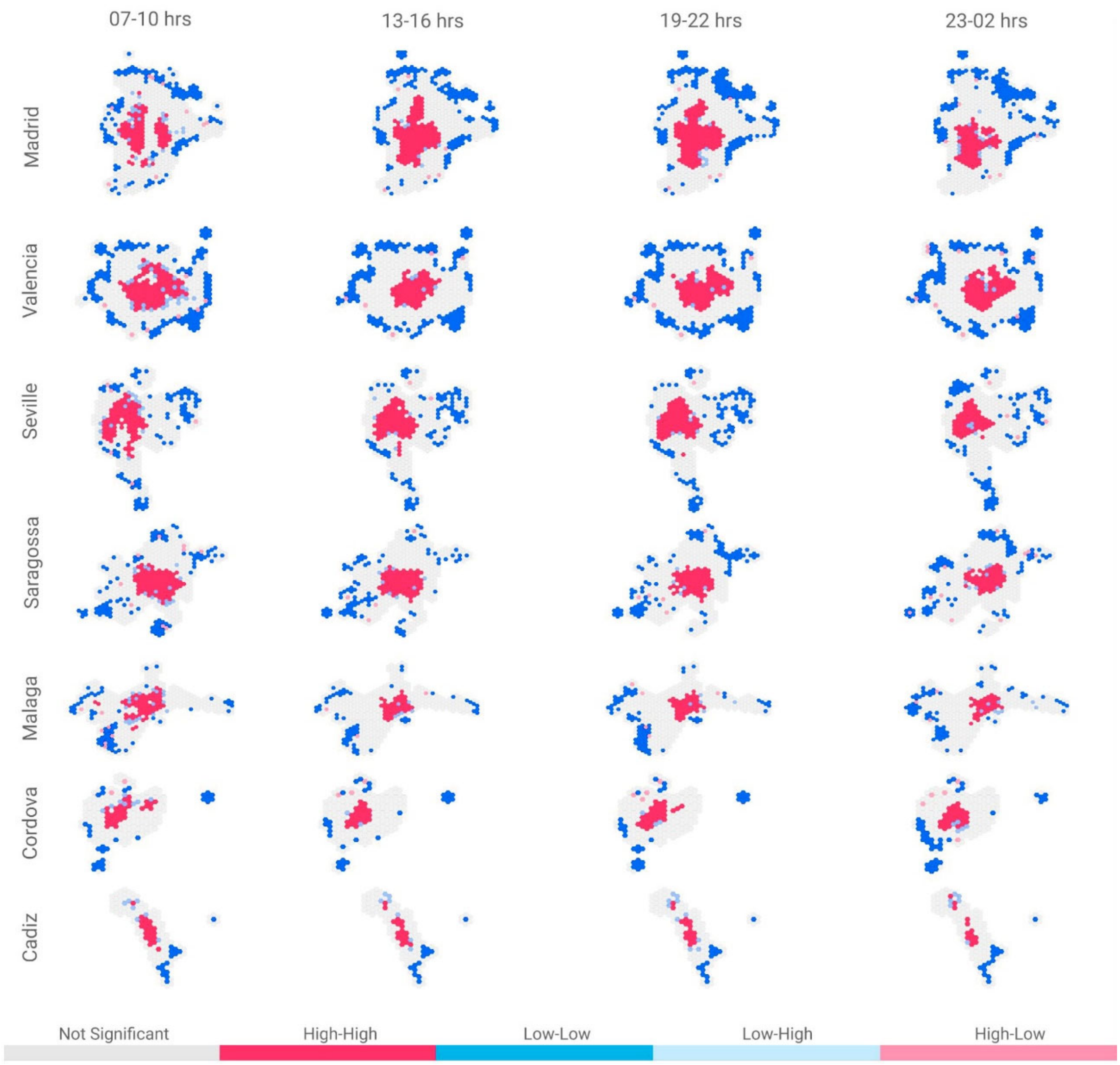

Fig 9- Bivariate LISA cluster maps for origins around destinations by time bands for working days. Source: the authors.

4.5 Spatial autocorrelation analysis: global trends

In order to better understand the system's spatio-temporal trends and assess its potential to be self-balanced, we graphed the calculated Global univariate and bivariate Moran's indices for each time band as seen in Figure 10. Most of the cities fall under the expected conceptual framework and their clustering degree is very similar in the central time bands (2 and 3), whereas origins are more clustered than destinations in late hours (band 4), and the opposite tends to occur in early hours (band 1). More interestingly, when observing the result from bivariate Global Moran's I statistics, the seven cities display the same dynamic: low values in early and late hours (07-10 and 23-02), since people are arriving at places where no trips are starting, and high values in midday and afternoon hours (13-16 and 19-22), since they are arriving at the same places where others are starting their trips. This dynamic makes the system less self-balanced during the first and last time bands, requiring moped redistribution, while band 2 and 3 are the hours when the system balances itself because mopeds are arriving where other users are starting their trips.

An exception, as we mentioned before, is Cadiz, which in general behaves as an outlier, most likely influenced by its particular urban structure, since its urban centre is located on a narrow peninsula, detached from peripheral residential areas.

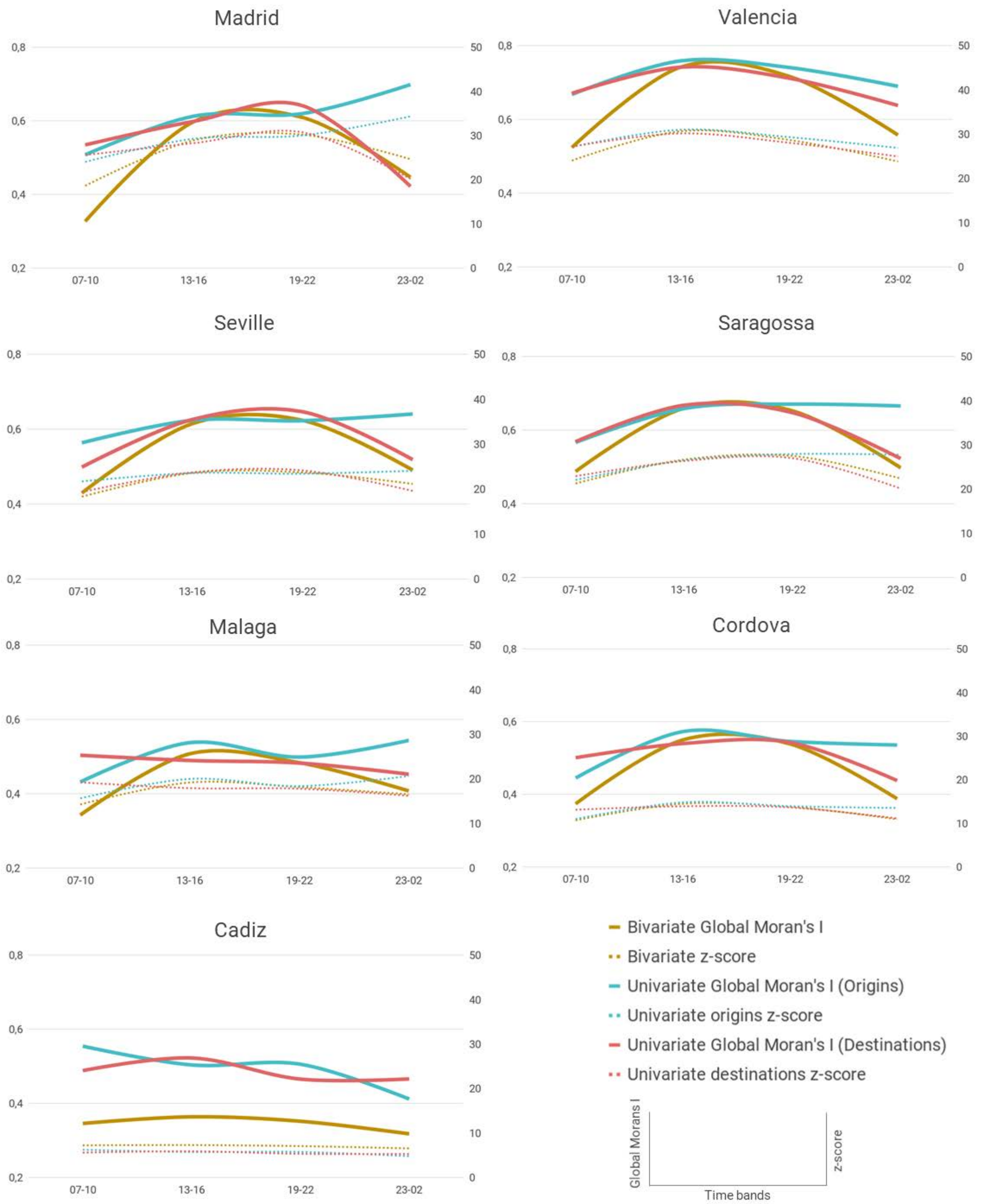

Fig 10- Global univariate and bivariate Moran Indices calculated for working days. Source: the authors.

The bivariate LISA results for working days also show how destinations in one time band are similar to origins in the following time band. When considering the results from the bivariate local Moran's I statistic between destinations and origins in all time bands, the highest numbers are found in the relationships of destinations with origins in the next time band (see Table 5).

	Origin (07-10 h)	Origin (13-16 h)	Origin (19-22 h)	Origin (23-02 h)
Madrid				
Destination (07-10 h)	0.327 (18.6)	0.529 (26.9)	0.486 (26.3)	0.393 (23.7)
Destination (13-16 h)	0.480 (24.5)	0.598 (28.9)	0.605 (29.6)	0.560 (30.1)
Destination (19-22 h)	0.516 (26.3)	0.574 (29.4)	0.610 (30.2)	0.626 (31.7)
Destination (23-02 h)	0.416 (21.4)	0.395 (21.8)	0.444 (23.6)	0.447 (24.7)
Valencia				
Destination (07-10 h)	0.524 (24.1)	0.705 (29.6)	0.655 (28.6)	0.584 (27.3)
Destination (13-16 h)	0.642 (28.0)	0.742 (30.7)	0.735 (30.0)	0.667 (28.4)
Destination (19-22 h)	0.652 (27.8)	0.681 (29.2)	0.717 (28.7)	0.680 (27.4)
Destination (23-02 h)	0.623 (26.3)	0.494 (23.6)	0.574 (25.2)	0.558 (23.9)
Seville				
Destination (07-10 h)	0.430 (18.3)	0.542 (21.5)	0.509 (21.0)	0.466 (20.5)
Destination (13-16 h)	0.561 (22.3)	0.615 (23.6)	0.620 (23.7)	0.589 (23.7)
Destination (19-22 h)	0.557 (22.8)	0.608 (23.9)	0.624 (23.7)	0.623 (24.0)
Destination (23-02 h)	0.524 (21.2)	0.504 (21.3)	0.525 (21.8)	0.491 (21.2)
Saragossa				
Destination (07-10 h)	0.488 (21.3)	0.595 (25.1)	0.593 (26.3)	0.571 (25.9)
Destination (13-16 h)	0.587 (24.2)	0.660 (26.7)	0.661 (27.5)	0.628 (27.1)
Destination (19-22 h)	0.562 (24.6)	0.639 (27.1)	0.653 (27.5)	0.641 (27.4)
Destination (23-02 h)	0.537 (22.3)	0.534 (23.2)	0.532 (23.5)	0.498 (22.4)
Malaga				
Destination (07-10 h)	0.343 (14.3)	0.505 (19.8)	0.465 (18.7)	0.445 (18.9)
Destination (13-16 h)	0.414 (16.2)	0.508 (19.2)	0.495 (18.6)	0.484 (19.1)
Destination (19-22 h)	0.412 (16.2)	0.486 (18.8)	0.484 (18.2)	0.494 (19.1)
Destination (23-02 h)	0.424 (16.7)	0.394 (16.3)	0.413 (16.7)	0.408 (16.6)
Cordova				
Destination (07-10 h)	0.374 (10.7)	0.526 (14.1)	0.493 (13.5)	0.471 (13.4)
Destination (13-16 h)	0.446 (11.9)	0.550 (14.5)	0.544 (14.2)	0.512 (13.8)
Destination (19-22 h)	0.432 (11.6)	0.546 (14.4)	0.539 (13.8)	0.520 (13.6)
Destination (23-02 h)	0.428 (11.3)	0.442 (12.4)	0.460 (12.4)	0.388 (11.0)
Cadiz				
Destination (07-10 h)	0.346 (7.2)	0.330 (6.8)	0.324 (6.8)	0.289 (6.3)
Destination (13-16 h)	0.398 (8.0)	0.364 (7.3)	0.363 (7.3)	0.318 (6.7)
Destination (19-22 h)	0.377 (7.7)	0.352 (7.1)	0.352 (7.1)	0.318 (6.5)
Destination (23-02 h)	0.401 (8.1)	0.365 (7.4)	0.366 (7.4)	0.318 (6.6)

Table 5 - Bivariate Moran's I (z-score) between destinations and origins for all time bands on working days. Source: the authors.

4.6 Relationship between spatial patterns and number of vehicles used

To explore the possible relationship between potential vehicle rotation and the number of vehicles used, we graphed the bivariate Global Moran’s I results with the percentage of vehicles used by time band on working days (see Figure 11). A clear relationship was revealed, as the resulting curves tend to follow a similar pattern throughout the day for all the cities. Nevertheless, all the cities show a peak in the percentage of vehicles used around band 3 (19-22 hrs), while the peak for the bivariate results is in band 2 (13-16 hrs).

Consequently, potential vehicle rotation could support and stimulate a higher number of trips, but not determine it. The number of trips would be the result of a high demand and high moped availability and proximity, increased when origins and destinations are closed to each other. Therefore, operators should foster this dynamic, especially in band 2 and 3.

These differences between time bands are important when operators need to know how many vehicles to deploy according to the day of the week. Hence, operators could adjust their logistics to respond to the different dynamics, which could reduce and optimise their distribution tasks.

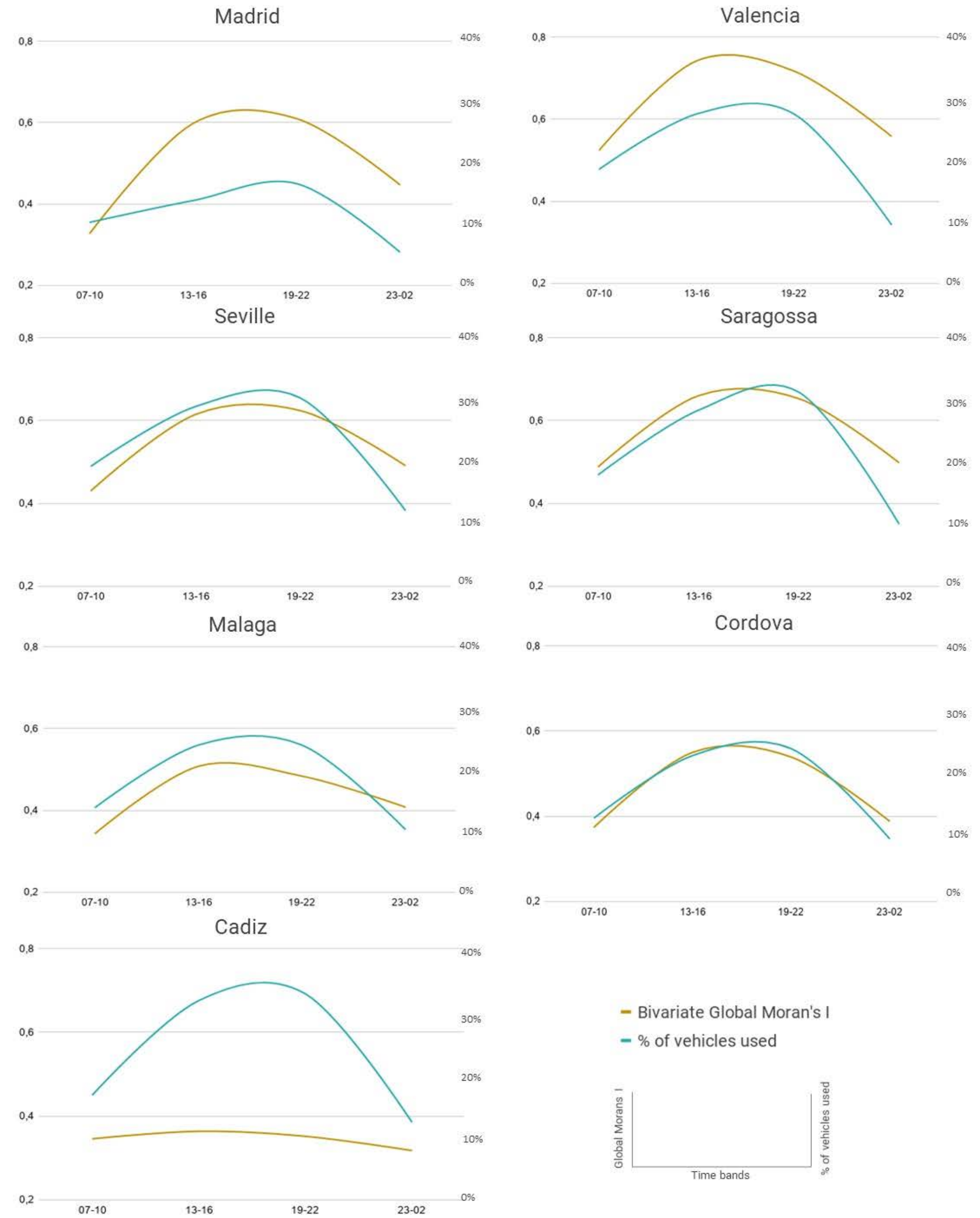

Fig 11- Bivariate Moran vs. percentage of vehicles used (working days). Source: the authors.

5. CONCLUSIONS

Based on GPS data collected, this paper explored the different dynamics of a moped-style scooter sharing service in urban areas over the course of a day. The research provides valuable information regarding the temporal and spatial patterns of this scarcely-studied micromobility service.

More importantly, it proposes a useful methodology based on the use of ESDA tools to understand travel patterns, increasing our knowledge of where demand comes from, when the service's peaks and valleys take place, popular destinations, the extent to which the system is potentially self-balanced, and how this is related to the percentage of vehicles being used. All these are insights that contribute to making better decisions in the shared mobility sector.

A considerable number of users have subscribed to moped services and use this shared mode even across different cities, which is an interesting fact related to the introduction of new concepts like mobility as a service beyond the city scale.

They ride mopeds mostly during warmer months in spring (May-June) and October when daily routines start. The dynamics revealed respond to certain patterns and variations that could be closely related to the existing land-use distribution in each city. In general, the spatio-temporal patterns identified correspond to what could be expected according to the conceptual framework initially outlined. We have learned that similarly to bicycles, mopeds are generally used for short urban trips (around 3.5 km). However, average speed is significantly higher for mopeds in comparison with cycling (14.3 kph in the case of bikeshare and 18.2 kph in the case of mopeds) (Romanillos & Gutiérrez, 2019). This fact makes this mode an attractive alternative, especially for cities like Madrid, which are not completely flat.

We have also demonstrated that time band 2 and 3 (13-16 and 19-22) are the most profitable hours for shared mopeds, as vehicle rotation (trip start and end locations are nearer) and the number of vehicles used are higher.

Our methodology also allowed us to identify when demand is more clustered (HH clusters in the univariate analysis) and more self-balanced (HH clusters in the bivariate analysis), pointing to the most profitable areas within the cities, and other areas where demand is particularly low (LL clusters) or not self-balanced (HL outliers). The assessment of both, the location of demand hubs, and the extent to which the system can balance itself, are important aspects to consider when planning and managing these micromobility services.

Our exploration results are useful for operators and authorities to make better decisions related to shared mobility services, especially in the post-pandemic era, when most of them are experiencing a worldwide boom (Ardila-Gomez, 2020; Harrabin, 2020).

As a clean alternative to cars, knowing where moped trips mostly start and end could have an impact on the infrastructure offered to improve the service and promote intermodality with mass transit.

Our study also demonstrated the importance of analysing and representing the dynamics of mopeds over time and illustrating activity during working days and weekends, which provides relevant knowledge when promoting policies or measures for specific periods of time. The fact that our methodology was tried in different cities allowed for comparisons and demonstrated that our methods are replicable.

Since our study was based on the dataset provided by one of the many moped-style scooter-sharing operators, it is important to consider that, while the sample is absolutely representative in small- and medium-sized cities where no other companies besides

Muving operate (we have all records), this is not the case for Madrid, Valencia, Seville, and Saragossa, which have more than one moped operator. In these cities, results must be carefully interpreted, as we are not covering the entire available moped fleet. When considering Madrid, Muving represented 14% of the available moped fleet during 2019, 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. Nevertheless, the dataset allowed us to glean more meaningful insights into a sharing sector that has not been exhaustively studied.

Future studies could complement our study by analysing the all moped-sharing services in cities with more than one operator, and even by considering other shared services, in order to holistically comprehend what basically conforms the interconnected

Mobility as a Service network. Future research lines could also focus on monitoring travel behaviour in the coming months and even years, monitoring and visualising the impact of the COVID-19 pandemic on the use of this and other shared modes.

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