Access and egress times to high-speed rail stations: a spatiotemporal accessibility analysis

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ABSTRACT

Accessibility by high-speed rail (HSR) depends not only on station-to-station travel time, but also on access and egress times, which can be determining factors in total journey travel time. However, studies focusing on accessibility analyses of access/egress times to/from stations are less extended in the literature and centre mainly on the influence of access times to stations on HSR accessibility levels on a regional scale. This paper's aim is to evaluate the importance of access and egress times to/from HSR stations in an urban context. We carry out a spatiotemporal accessibility analysis that considers the temporal variations of both taxi and public transport travel times. General Transit Feed Specification (GTFS) files for public transport and TomTom Speed Profiles data for cars are used to measure access/egress times. These kinds of data allow for the calculation of travel times from/to HSR stations through network analysis GIS tools at different times of the day, and thus a spatiotemporal accessibility measure can be obtained. This accessibility measure is complemented by a mass factors representing the activity 'hotspots' in the visited city throughout the workday, which is derived from Twitter data, while population is considered for city of residence. This method was applied to the two largest metropolitan areas in Spain: Madrid and Barcelona, where the influence of access/egress times acquires a higher relevance for rail-based trips. The results obtained show that access and egress times vary significantly during the day, depending on the levels of traffic congestion and the frequency of public transport services, which are always more favourable for taxis. In addition, weighted average access and egress times at the home end are higher than those at the activity end since population tends to show more dispersed spatial patterns than activities. Another interesting finding is that the first and last mile of the HSR trip usually account for a high percentage increase in travel time (about 35% for taxis and 55% for public transport, respectively). These results have important policy implications. The paper suggests that HSR accessibility can be improved also by improving local transport services, scheduling coordination and land use policies.

Keywords: Access to stations; high-speed rail; spatiotemporal accessibility; Big Data

1. INTRODUCTION

High-speed rail (HSR) networks are becoming fully developed transport systems encompassing a large number of cities and offering different services adapted to the purposes of the trip. However, there is an imbalance in the quality of service given to different cities in the network. Apart from the differences in service-related aspects, such as speed, frequencies, or ticket fares (Moyano and Coronado, 2018), the location of the station and its integration in urban public transport networks are identified as key factors related to the global quality of the rail connection (Brons et al., 2009; Givoni and Rietveld, 2007).

Many studies have focused on the station's location. Peripheral stations, located on a high-speed line out of the city make the connection to/from the city centre difficult, while central and edge stations are potentially better integrated with the city, notably in terms of access by non-motorised modes and public transport (Moyano et al., 2018; Troin, 2010). Nevertheless, in the case of large metropolitan areas even benefiting from a central and well-integrated HSR station, access and egress times can be very high due to the mere urban extension or low quality of urban transport systems in certain city areas.

The duration of a trip is a determinant for choosing HSR as a travel alternative (Keijer and Rietveld, 2000; Rietveld, 2000). For that reason, in some of the most critical timing routes, there is significant concern about reducing in-vehicle travel times in an attempt to gain some minutes to compete with air transportation (Vickerman, 2015). At the same time, there is much less concern about the time spent on access/egress times to HSR stations and the quality of intermodality in the station itself (Tapiador et al., 2009). However, access/egress times can tip the scale in favour of choosing one or another mode of transportation and, in some cases (Martín et al., 2014), it is more effective to make an effort (and investment) to improve accessibility to/from stations than applying this effort to improve HSR in-vehicle journeys (thereby, diminishing in-vehicle travel time). In fact, when HSR travel times are evaluated, consideration should be given not just to in-vehicle travel times but, more importantly, to door-to-door travel times and their variations in time (temporal variations during the day) and space (differences depending on the origin and final destination in the whole HSR trip). However, there are no examples in the literature that analyse this question in detail.

This paper aims to perform a spatiotemporal analysis of access and egress times to/from HSR stations within metropolitan areas, and then to assess the influence of access/egress times in the whole HSR door-to-door trip. For the first time, the authors conduct a spatiotemporal accessibility analysis to/from HSR stations for both taxis and public transport, and precisely calculate the influence of the first and last mile of HSR trips using new Big Data sources. The results obtained have important implications for local transport and land use policies. Inter-urban accessibility can be decisively improved through actions at the local level.

The remainder of this paper is structured as follows. Section 2 summarises the existing literature on HSR accessibility, particularly from the point of view of HSR stations access and egress times, and on the use of Big Data sources in accessibility studies. Section 3 describes the data and the methodology. Section 4 shows the main results regarding the temporal and spatial analysis of access and egress times to/from high-speed rail stations, and their influence on the total travel time between Madrid and Barcelona. Second, this section discusses the dynamics of access and egress times to/from stations, comparing between transport modes. Finally, Section 5 presents the main conclusions of the study.

2. LITERATURE REVIEW

2.1. High-speed rail accessibility: the importance of access/egress times to/from stations

High-speed rail accessibility studies are widely extended in the literature and focus mainly on the remarkable reduction in travel time this infrastructure enables (when it is accompanied by adequate services). These studies are very useful for understanding changes in regional accessibility generated by the new infrastructure in the cities it serves (Cao et al., 2013; Chang and Lee, 2008; Gutiérrez, 2001; Gutiérrez et al., 1996) or even for assessing different scenarios of network development (Jiao et al., 2014; Monzón et al., 2013). These studies assess accessibility improvements by using different indicators, all of them based on a station-to-station measure of travel time impedance. Some of these analyses tend to assume that the influence of an HSR system on accessibility extends far beyond each station because these indicators are applied to extensive surfaces, which could be regarded as an overestimation of accessibility in spatial terms (Martínez Sánchez-Mateos and Givoni, 2012). However, accessibility effects derived from HSR depend not only on station-to-station travel time, but also on access and egress times to/from HSR stations. In fact, the influence of the first and last mile can be a determinant in door-to-door HSR trips (Monzón et al., 2016), but are generally ignored in HSR accessibility studies. Monzón et al.'s (2016) paper had the merit of putting this issue in the foreground, but they calculated static access travel times in a relatively simple way from the centroids of the municipalities to the railway stations.

Access/egress times are particularly important in studies on modal choice between HSR and air transport. The main aim of these studies is not centred on access/egress times but on an analysis of air and high-speed rail competition (Dobruszkes, 2011; Román et al., 2007), where the stations/terminals' intermodality will be a determinant. In these studies, the access/egress time to/from stations and terminals is considered an average static measure conditioning user's mode choice: the less time taken from the origin of the trip in the home end (city of residence) and from the final destination in the activity end (visited city), the higher the probability of using one transport mode over another. One exception is a study by Martín et al. (2014), which considers different probabilities according to the spatial variability of access/egress times within the origin and destination metropolitan areas. Apart from this study, there are many others that assess users' choice of travel mode to conventional railway stations. Most of these studies focus on analyses of the different transport modes determining the local modal share, analysing the profile of the access/egress modes on journeys to and from railway stations (Givoni and Rietveld, 2007) and evaluating the predisposition to use railway services (Keijer and Rietveld, 2000), and how important the ‘access-to-the-station’ part of a rail journey is to passengers (Brons et al., 2009). Other, more specific, studies evaluate the role of the bicycle as a feeding mode to railway stations, as an interesting alternative for multimodal trips (Martens, 2004; Rietveld, 2000).

Examples of analyses on access/egress times to/from HSR stations are less extended in the literature, although the importance of stations’ local accessibility and their integration in the urban transport network are determinants in the assessment of high-speed rail trips. In fact, even benefiting from good local accessibility, access and egress times to/from HSR stations may be very high, especially in large metropolitan areas. They may experience high variations, depending on the time of the day and the transport mode chosen to reach or leave a station. Big Data sources offer new opportunities for spatiotemporal analyses of access and egress times and for the evaluation of their importance in total travel time for HSR travellers.

2.2. Big Data sources in accessibility studies

Dynamic accessibility measures are focused on the assessment of temporal variations in transportation travel times, due mainly to traffic congestion in the case of private vehicles, and due to frequencies and the adaptability of schedules in the case of public transport. In these analyses, new data sources (so-called Big Data sources) play an important role. New studies on transport accessibility and mobility have started to introduce this kind of data in their analyses. For instance, applications such as Google Maps Traffic Overlay and TomTom Live Traffic allow for collecting information such as traffic volume, average traffic speed, and actual journey times (Bartosiewicz and Wisniewski, 2015). Also, TomTom’s historical information provides actual observed data on the daily variations in speed profiles for automobiles, allowing for an assessment of congestion impacts on accessibility (Moya-Gómez and García-Palomares, 2015 and 2017) or even an analysis of risk severity in transportation networks. These are defined as the effects of a link or network failure on the whole system (Cui and Levinson, 2017). Concerning public transport, variations on transit service frequencies are a key factor for dynamic accessibility analysis. In this sense, the General Transit Feed Specification provides a common format for public transportation schedules and associated geographic information (routes, stops, etc.), which is a very useful data that can be used in travellers’ routing analyses. Such data have been used in recent transit research since Google launched the open platform in 2008. Some studies have used this data to evaluate transit accessibility in different metropolitan areas (Bok and Kwon, 2016; Farber et al., 2014) and compare it to that provided by cars (Salonen and Toivonen, 2013). Other studies have focused on analysis of the influence of transfers and timetables on transit accessibility (Hadas and Ranjitkar, 2012) and even of transit circuity (Huang and Levinson, 2015) to better understand the performance of public transport systems.

In addition to network performance, the analysis of daily accessibility should also incorporate the effect of the mass (attractiveness) of destinations. Most accessibility studies consider population or employment as mass factors (for example, Boisjoly and El-Geneidy, 2016; Merlin and Hu, 2017; Moya-Gómez and García-Palomares, 2017), but recently new data sources (Twitter) have also been used to reflect the attractiveness of destinations (García-Palomares et al., 2018). In contrast to these papers, our study focuses on the first and last mile of door-to-door HSR trips. Spatiotemporal accessibility by both public transport and taxis is measured using GTFS files and TomTom Speed Profiles data, respectively. The attractiveness of the activity end (visited city) is estimated through Twitter data using a new methodology that allows us to identify the areas visited by travellers in the visited city.

New data sources such as Twitter present certain advantages compared to traditional data sources. First, such information should reflect the location of the relevant city's main activity areas (areas in which there is a concentration of workers, tourists and/or residents) and allow for the measurement of temporal variations in these daily activities' hotspots. These social media data provide a large volume of spatiotemporal digital footprints[1], which are a valuable source of knowledge about the physical environment and social phenomena (Li et al., 2013). The usefulness of Twitter data to understand and quantify mobility patterns has been demonstrated in previous papers (Hawelka et al., 2014; Luo et al., 2016; Salas-Olmedo and Quezada, 2016). In contrast, traditional data sources (census and/or employment, for instance) are static measures of cities' activity: Census data offer information on the spatial distribution of the population at night (place of residence) but not on their location throughout the day, while employment data are used as a proxy for population distribution during the day and ignores the fact that many people are at home during the day. Second, an important advantage of using these new sources of information (Twitter or similar) is that the data provided are comparable for cities during the same period; however, it is sometimes difficult to obtain updated employment data for the different case studies analysed. The main drawback of Twitter data is its bias, given that the penetration of this social network is different according to social groups[2]. A more accurate data source for measuring the attractiveness of destinations is mobile phone records; however, obtaining this kind of data is very difficult due to its potentialities. In addition, even with mobile phone data, there are numerous potential biases and uncertainties, since the whole population (and thus all mobility patterns) is not fully covered (see Bonnel et al., 2015; Wang et al., 2018). In any case, the methodology proposed in the next section allows obtaining consistent results and it could also be applied in a similar way to both Twitter and mobile phone data.

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[1] Twitter activity is represented by people sending tweets.

[2] Twitter users' characteristics (Twitter, 2016) (between brackets: national average):
a) Gender: male 54% (49%)
b) Age: 16-24, 21% (12%); 25-34, 29% (18%); 35-44, 28% (19%); 45-54, 16% (16%); >55, 6% (35%)
c) Education: University studies 41% (22.5%)

3. DATA AND METHODS

3.1 Study areas delimitation

Our spatiotemporal approach was applied to the two largest metropolitan areas in Spain: Madrid and Barcelona, where the influence of access/egress times is highly relevant for rail-based trips. We consider the high-speed rail stations of Puerta de Atocha in Madrid and Sants in Barcelona. These stations have been chosen in this study because all the HSR connections between Madrid and Barcelona are made from/to them.

The delimitation used in this paper was the area composed by all the municipalities that have more than 50% of their territory within a density isoline of 500 inhabitants/km^2 from the main city (Moya-Gómez and García-Palomares, 2015). This isoline was generated with the density kernel ArcGIS tool, using the 1 km^2 European Environment Agency of the European Union (EEA) reference grid with Eurostat population data. As there is no unique definition of the extension of a metropolitan area, the delimitation used in this paper was defined following similar criteria than those used in the MUAs definition (Morphological Urban Areas, IGEAT, ESPON Database Project), but in this case, less population-dense areas are included, softening the influence of 'border effects'.

As a result, in the case of Madrid, the study area encompasses 5,801,809 inhabitants, 2,312 km^2 and 39 municipalities, while the metropolitan area of Barcelona has 4,462,615 inhabitants, 1,420 km^2 and 88 municipalities (Figure 1).

3.2 Data collection: Travel times and weights

Travel time data used in this paper were obtained from different sources. Data for public transport (timetables, routes, trips, stops, etc.) were obtained from the GTFS files provided by different urban and regional transit agencies and operators[3] dated November 23, 2016. This public transport data were complemented with a pedestrian network, which will allow modelling real pedestrian access to public transport stations and stops. The pedestrian network was obtained from Open Transport Map data. In this paper, 70 m/min is considered the average walking speed (Salonen and Toivonen, 2013). Finally, both pedestrian and GTFS data were integrated to develop the whole public transport network through the routing calculation extension 'Network analyst' of the GIS software ArcGIS 10.3.

Concerning the road network, this study used TomTom Speed Profiles data, obtained from the average journey times reported from users' navigation devices. The Historic Speed Profiles are defined as a percentage every five minutes with respect to the observed free-flow speed of the arc. This data structure has been prepared to be used with ArcGIS 10.3. Once the private vehicle travel times were obtained, they were increased by 10 minutes in order to simulate the

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[3] Madrid Transport Authority (Consorcio Regional de Transportes de Madrid) for Madrid and different sources for Barcelona: urban buses and metro operators (TMB), metro and commuting metro (FGC), commuting train (Renfe), tramways (TRAM), and all operators of buses of the Metropolitan Region (AMB).

time spent walking from home to take the taxi and then to pay and walk from the taxi to the station.

The origins/destinations for the access/egress time analysis are the centroids of cells in the 1x1 km grid[4], which follows the pattern of the EEA grid but includes not only the cells of the city with population but also those with Twitter users (Figure 1). Population data, obtained from Eurostat population data from 2011, were used for considering the weights of the cells in the home end of the trip (city of residence). Twitter data should reflect the attractiveness of the cells in the activity end (visited city).

Figure 1: Study area delimitation in Madrid and Barcelona: Population and Twitter users' distribution

Available Twitter data encompass all the free-downloaded geolocated tweets registered in the Madrid and Barcelona study areas from April 2016 to March 2017. As the activity hotspots are represented mainly by users, that is, people doing their daily activities in certain parts of the city, the data of total tweets needs to be filtered. Data treatment includes first, the removal of those tweets corresponding to enterprises or robots, and second, the identification of the number of users in each cell of the study area every five minutes throughout the day. In addition, the rationale for using Twitter data is that it detects travellers at their destination. As the aim of this paper is to evaluate access and egress times to/from HSR stations in the Madrid-Barcelona connection, the attractiveness of the destinations will be represented only by those users identified as residents in the city of origin in an attempt to simulate the potential destinations of people travelling between those cities. Some studies that have analysed users' locations within a city define 'home' as the place most frequently 'visited' by a user at night time (García-Palomares et al., 2018; Luo et al., 2016; Salas-Olmedo and Quezada, 2016). Since we are considering two cities (Madrid and Barcelona), we infer the city of residence of each Twitter user considering the city in which the user is more frequently registered during the night[5]. Finally, the average value of Twitter users between 8:00 and 22:00 hours in each cell of the visited city is obtained in order to measure the cells' attractiveness for HSR travellers.

As Figure 1 shows, the distribution of Twitter users, represented only by those travelling between Madrid and Barcelona at their destinations, allows us to detect potential destinations consistent with what was expected – working areas on the periphery, and especially the city cores, are identified as high-activity areas.

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[4] In this paper, we have used the centroids as an automatic procedure for calculations. However, the authors recognise that the centroid could not be representative of the population or activity distribution in each cell, especially in less dense areas located on the periphery of the study areas. For further research, a deeper analysis of the optimal centre of mass for each cell should be included.

[5] The mode is used as the statistical means for identifying the place of residence for Twitter users.

3.3 Travel time measures

The proposed methodology is based on a computation of spatiotemporal measures of travel time every five minutes, from 6:00 to 00:00. This every-five-minutes calculation increases computational complexity but provides a precise representation of the evolution of travel times and accessibility during the day.

These travel time measures are analysed temporally and spatially for access/egress to/from stations considering both taxis and public transport. A weighted average measure is calculated for both access (T_{ac}) and egress (T_{eg}) times (1)(2), considering the population in the home end (city of residence) and Twitter users in the activity end (visited city) as mass factors. It is conjectured that the outbound trip starts at home in the city of residence and finishes in an activity place in the visited city (Twitter data as a proxy for the activity in each cell), and vice versa for the inbound trip. Second, the total additional travel time (t_{ij}) due to access and egress times is computed (3) for a specific high-speed train departure/arrival time between all the possible combinations of origin/destination cells between Madrid and Barcelona and vice versa (Figure 2).

Outbound trip Inbound trip

$$T_{ac\,1} = \frac{\sum_i \left(t_{access\,i}{}^{HSR\,dt\,-\,t\,access\,i} . Po_i \right)}{\sum_i Po_i} \qquad T_{ac\,2} = \frac{\sum_i \left(t_{access\,i}{}^{HSR\,dt\,-\,t\,access\,i} . Tw_i \right)}{\sum_i Tw_i} \tag{1}$$

$$T_{eg\,1} = \frac{\sum_j \left(t_{egress\,j}{}^{HSR\,at} . Tw_j \right)}{\sum_j Tw_j} \qquad T_{eg\,2} = \frac{\sum_j \left(t_{egress\,j}{}^{HSR\,at} . Po_j \right)}{\sum_j Po_j} \tag{2}$$

$$t_{ij} = t_{access\,i}{}^{HSR\,dt\,-\,t\,access\,i} + t_{egress\,j}{}^{HSR\,at} \tag{3}$$

Where:

- $t_{access\,i}{}^{HSR\,dt\,-\,t\,access\,i}$ is the access time from cell i to the HSR station, computed considering the time needed to arrive at the station in order to take a specific HSR service ($HSR\ dt$ is the HSR departure time).
- $t_{egress\,j}{}^{HSR\,at}$ is the egress time from the HSR station to cell j, computed at the time of arrival of the specific HSR service ($HSR\ at$).
- Po is the population of each cell.
- Tw refers to the Twitter users in each cell during the day (temporal range between 8:00 -22:00 hours).

Figure 2: Origin/destination cells combination for assessing access+egress times

In addition, the disaggregation in the computation of travel times allows assessing the differences among cells in each city analysed. The average of travel times and their coefficient of variation during the day for each cell included in the study areas are obtained, for both access and egress times to/from stations. Also, the ratio between public transport and taxi travel times is computed for comparing the different performance of these transport modes in diverse peak and off-peak temporal scenarios.

4. RESULTS

4.1 Temporal variation in access and egress travel times to/from high-speed rail stations: Madrid and Barcelona

This subsection analyses the temporal variation during the day of access and egress travel times to/from high-speed rail stations for outbound trips, taking into account HSR departure and arrival times, respectively. Weighted access (T_{ac}) and egress (T_{eg}) times are computed in order to assess their influence on the whole HSR trip[6] (Figure 3), considering the access time for reaching the station before a specific HSR departure time and the egress time just after the HSR arrival at the destination. Access times are weighted by population of origin cells, and egress times by activity of destination cells.

In general, both cities present similar trends in terms of temporal variation during the day. Egress times are generally lower than access times on outbound trips, mainly because of the central location of the destinations (activity areas represented by Twitter users) compared to the more dispersed location of origins (population) in the case of access travel times. Taxis show a better performance than public transport, whose travel times are around 20 minutes longer. In addition, access and egress times are higher in Barcelona than in Madrid, for both taxis and public transport, although the difference between cities is only around 4-5 minutes.

Focusing on access times, the highest travel times by taxi (Figure 3a) are around 8:30 hours and 17:30 hours, with the first peak of the day being more pronounced. The most favourable time for public transport is the morning peak hour, when the frequency of public transport services is higher (Figure 3b) [7]. In contrast to the congestion suffered by accessing a station in the city of origin early in the morning, travellers do not experience congestion when arriving at their destination city (because the HSR trip Madrid–Barcelona and vice versa takes 2 hours and 30 minutes. The lowest values of egress times for taxis are found for HSR services arriving at

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[6] In order to avoid repetition, only access and egress times related to the outbound trip are shown in Figure 2.

[7] In this analysis, it has to be highlighted that, for public transport access times, the potential origins that are able to arrive at the station to take a train reach the 90% of the cells in the study area only after 8:00 hours in the case of Madrid and 8:30 hours in the case of Barcelona, because public transport services start at 6:00 hours in the morning. Before these times, the cells unable to reach the stations (distanced areas to the station) are not included in the weighted average and, for that reason, the travel times' trend diminishes in the very early hours of the day. In the case of egress travel times, all local trips depart at the same time, when the HSR service arrives at the station.

21:30 hours (Figure 3c). At that time, congestion starts to decrease, which benefits taxi services. The lowest values for public transport are found a bit earlier, around 18:00-19:00 hours, especially for egress times from Madrid-Atocha station. Finally, public transport egress times increase abruptly for HSR services arriving after 21:00 hours, particularly in Barcelona, when the frequency of public transport starts to decrease (Figure 3d).

Figure 3: Weighted average access ($T_{ac\,1}$) and egress ($T_{eg\,1}$) times for outbound trips.

Total weighted access + egress times ($T_{ac\,1}$+ $T_{eg\,1}$) for outbound trips are represented in Figure 3e and 3f. In general, both directions of HSR trips present similar trends throughout the day. For taxis, the early morning HSR trains are those that present higher access/egress times in sum, while public transport curves exhibit almost the opposite picture, with the morning peak hour being the most favourable. On the other hand, for train passengers arriving at around 22:00 hours, egress times are particularly low in taxis (free flow conditions) but very high in public transport (low frequencies).

Focusing on average travel times during the day (horizontal lines in Figures 3e and 3f), taxi services imply extra travel time due to local accessibility of 51.9 minutes (an increase of 34.6% in total travel time) in the case of the Madrid–Barcelona trip, and 50.9 minutes (a 33.9% increase) in the Barcelona–Madrid link[8]. For public transport, average values are around 30 minutes higher (88.8 minutes for the Madrid–Barcelona link and 85.3 for the Barcelona-Madrid connection) which represents an increase in travel time of between 59.2-56.8 % of travel time.

4.2 Spatial disparities in access and egress travel times

Figure 4 shows the spatial variation of access travel times[9] (average travel time during the day and coefficient of variation) for both public transport and taxis. Taxis almost reach the third part of the study area in less than 40 minutes and the whole metropolitan area in less than 60 minutes, both in Madrid and Barcelona. In the case of public transport, only the core of the cities and the main metro/commuter rail corridors allow for competition with taxis in terms of average travel time values. Nevertheless, although these more favourable areas for public transport are represented by a small number of cells in the study areas, they concentrate high volumes of population (Table 1). For instance, in the case of Madrid, the cells that can access the station in less than 45 minutes represent only 9.1% of the total area (S), but they encompass around 52% of the population (Po) considered in the analysis. In a similar way, in Barcelona these percentages are around 10.2 % of the total area and 55% of the whole population.

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[8] Considering 2h 30 minutes of HSR in-vehicle travel time

[9] Because of space limitations, Figure 4 shows only access travel times. Maps of egress travel times are very similar.

Figure 4: Average access travel time value and coefficient of variation for taxis and public transport

Table 1. Percentage of population (Po) and area (S) involved by transport mode and travel time interval

	Madrid				Barcelona			
Transport mode	**Ta**		**PT**		**Ta**		**PT**	
Ttravel (min)	*%Po*	*%S*	*%Po*	*%S*	*%Po*	*%S*	*%Po*	*%S*
< 15	4.5	0.4	1.5	0.2	4.9	0.3	5.6	0.4
15 – 30	66.0	28.3	18.6	2.1	50.8	18.1	25.0	3.1
30 – 45	28.2	57.0	32.4	6.8	40.2	56.7	24.5	6.7
45 – 60	1.3	13.7	27.5	11.8	4.1	23.6	10.1	10.1
60 – 90	0.0	0.5	16.3	27.6	0.0	1.1	10.3	23.9
90 – 120	0.0	0.0	2.1	22.9	0.0	0.1	20.7	21.4
> 120	0.0	0.0	1.6	28.6	0.0	0.0	3.8	34.4

Coefficients of variation reflect the temporal variability of performance of the networks in accessing railway stations (Figure 4). Public transport exhibits high values in certain distant areas, reflecting fluctuations in public transport frequencies. The coefficients of variation of taxi travel times are more homogenously distributed, but some spatial disparities can be observed, according to the congestion levels experienced in each area. Supplementary videos related to temporal variations of travel times for both taxi and public transport can be found in the supplementary material of this paper.

Total local travel times (access + egress) vary not only temporally (Subsection 4.1) but also spatially, depending on the location of the different origins/destinations and their connectivity, both for road and public transport networks. To catch all these spatial differences, the total amount of time spent accessing and egressing stations (t_{ij}) for all the O/D combinations is represented by quintiles in Table 2, for specific outbound and inbound high-speed trains:

Table 2. Total access + egress times (minutes) by taxi (Ta) and public transport (PT) according to OD combinations in outbound (Out) and inbound (In) trips: quintiles (P)

Round trip:	**Madrid – Barcelona – Madrid**				**Barcelona – Madrid – Barcelona**			
HSR timetables	*Outbound 9:00 h – 11:45 h* *Inbound 18:25 h – 20:55 h*				*Outbound 9:00 h – 11:45 h* *Inbound 18:30 h – 21:20 h*			
	P20	**P40**	**P60**	**P80**	**P20**	**P40**	**P60**	**P80**
Ta (Out)	49.9	56.1	61.7	68.5	48.7	54.8	60.1	66.2
Ta (In)	48.4	54.1	59.4	65.8	46.1	51.6	56.6	62.7
PT (Out)	79.0	94.3	108.5	126.3	73.3	87.6	100.3	115.7
PT (In)	77.9	93.3	108.2	127.9	75.3	90.4	104.1	120.4

In general, there are no important differences in total access+egress times between Madrid–Barcelona round trips or vice versa, as expected. However, significant differences are found between public transport (PT) and taxi (Ta). In the first quintile (P20), the differences between travel times by transport mode are around 25-30 minutes higher for public transport. These O/D combinations represent connections between central areas that are well covered by public transport services (as shown in Figure 4). The last quintile (P80) includes the combination of distanced and low-served (especially by metro/commuter rail) cells of the metropolitan areas, where total travel times increase around 2 hours by public transport and 65 minutes by taxi.

When comparing outbound and inbound trips, taxi travel times mean values are slightly higher in both cities for outbound trips, due to the more significant traffic congestion in the morning peak hour. For the inbound trip, access times may be also affected by the afternoon peak hour, but the egress time from the stations at the end of the day (around 21:00 hours), when traffic can run almost in free flow, decreases the total access+egress times for taxis. Concerning public transport, depending on the direction of the trip, the performance is nearly the opposite. In the Madrid–Barcelona round trip, public transport travel times are slightly lower for the inbound trip (HSR departure time at 18:25 hours), because the egress time from Madrid–Atocha at around 21:00 hours is still competitive and starts to increase sometime after that (see Figure 3d). However, considering the Barcelona–Madrid round trip, for inbound trips arriving in the evening there is an increase in public transport travel times due to the lower frequencies supplied.

4.3 Comparison between transport modes: travel time ratio public transport/taxi

The public transport/taxi travel time ratio allows for a temporal and spatial comparison of the performance between taxis and public transport in accessing HSR stations (Figure 5). The temporal variation of this ratio shows that, on average, the values are higher than one, since taxi travel times are clearly lower than those by public transport (Figure 5a). However, there are some differences, depending on the time of day analysed. First, the morning peak hour is the most favourable for public transport for both cities because of the higher levels of congestion for private transport and the higher frequencies of public transport at this time. Second, in off-peak hours (12:00 hours), taxi travel time rises to its highest competitiveness. This travel time ratio shows a similar temporal pattern in both cities and is always lower in Barcelona than in Madrid.

Figure 5: Access time ratio public transport/taxi: temporal (a) and spatial (b) variation

Travel time ratios between public transport and taxis can also be analysed spatially (Figure 5b). As expected, the lowest ratios (better performance of public transport) are found within the city centre and along the main public transport corridors, since these areas are well served, mainly by metro and rail. Cells showing particularly low values along the corridors correspond to the location of commuter train stations. In the comparison of the different time slots, higher changes can be identified in some distant cells, influenced by the effect of significantly lower public transport frequencies during the noon off-peak period. These changes are higher in Madrid than in Barcelona. For instance, in Madrid, the population involved in areas with ratios lower than 1.50 in the 8:30 h scenario rises to 49.3% while it decreases to around 31% of the total population in the 12:00 h scenario (Table 3). In Barcelona, the differences are smaller but also remarkable, reaching 65.4% of population, with ratios lower than 1.50 in the first scenario and diminishing to 58.8% in the off-peak hour. In both cities, the 17:30 h scenario shows an intermediate situation in terms of both population and area.

Table 3. Percentage of population (Po) and area (S) involved by scenario and ratio interval.

	MAD						BCN					
Scenario	**8:30 h**		**12:00 h**		**17:30 h**		**8:30 h**		**12:00 h**		**17:30 h**	
Ratio	*%Po*	*%S*	*%Po*	*%S*	*%Po*	*%S*	*%Po*	*%S*	*%Po*	*%S*	*%Po*	*%S*
<1.00	4.0	0.6	3.2	0.3	2.7	0.3	13.7	1.2	12.2	1.0	12.1	1.0
1.00 – 1.50	45.3	11.7	27.8	5.1	33.1	6.8	51.7	14.8	46.6	11.1	50.5	12.8
1.50 – 2.00	41.0	26.9	53.2	23.0	51.4	24.6	24.7	24.3	26.2	20.8	24.6	22.7
2.00 – 2.50	7.0	22.4	11.6	23.4	9.4	23.0	4.6	22.1	8.5	21.2	6.6	20.4
> 2.50	2.5	28.7	4.2	48.2	3.4	45.3	4.0	27.2	6.5	45.8	6.2	43.1
N*	0.2	9.7	0.0	0.0	0.0	0.0	1.3	10.4	0.0	0.0	0.0	0.0

*Percentage of population/areas that cannot access the station by public transport for a certain scenario

5. CONCLUSIONS

Access and egress times are determining factors in door-to-door high-speed rail trips. HSR competitiveness depends not only on in-vehicle travel times, timetables and fares, but also on the characteristics and efficiency of local accessibility. Although the first and last miles may represent a significant share of the total journey's travel time, especially in large metropolitan areas, access and egress times have been scarcely studied in the literature.

This paper analyses the spatiotemporal variations during the day of access/egress times to/from HSR stations in the two largest metropolitan areas in Spain, Madrid and Barcelona. Nowadays, reliable travel time data, such as GTFS (General Transit Feed Specifications) for public transport and TomTom Speed Profiles data for private vehicles, and computational capacity allow scholars to carry out in-depth travel time dynamic analyses. In addition, new data sources such as mobile phone records and social media data (such as Twitter) allow for the tracking of individuals. In our case, using data from Twitter made it possible to ascertain the places most visited in Barcelona by travellers from Madrid and places most visited in Madrid by travellers from Barcelona. This variable has been included in an accessibility indicator to analyse the desirability of destinations.

The results obtained show that access and egress times vary significantly throughout the day, depending on variations in traffic congestion and the frequency of public transport services, which always favour taxi services. In addition, weighted average access and egress times in the home end are higher than those in the activity end, since population tends to show more dispersed spatial patterns than activities. Another interesting finding is that the first and last mile of the HSR trip account for a high percentage of the total travel time (about 35% or 55% for taxis and public transport, respectively).

Both Madrid and Barcelona present similar patterns in the temporal variation of access/egress travel times, with slightly higher values of travel times in Barcelona, both for taxis and public transport. In relation to spatial variations, the results allow us to identify areas in the cities that present higher/lesser levels of congestion at certain times of the day or better/worse public transport services. The temporal variation in taxi travel times (access and egress) is low, which reveals very low levels of congestion in both cities. These results are consistent with the paper by Moya-Gómez and García-Palomares (2017) comparing congestion levels in several European cities, with Madrid and Barcelona being the least congested cities in the sample. This fact is due both to large infrastructure investments in both cities before the economic crisis and to the sharp drop in annual average daily traffic during the economic crisis. In contrast, the spatial variation of local taxi travel times is very high, reflecting the relatively large size of both metropolitan areas.

These aspects have important policy implications. First, in the analysis of HSR accessibility, not only the average, but also the temporal and spatial variations of access and egress times must be considered as key factors in door-to-door HSR trips. HSR analysis should consider intermodal approaches, and not only the station-to-station approach, to assess the real impacts of HSR on accessibility improvements. In addition, this kind of analysis could help urban and regional transport authorities to detect deficiencies concerning station integration in metropolitan transport systems and to evaluate the implications of local accessibility improvements, such as opening of new metro lines or improving scheduling coordination between suburban trains and HSR services.

The results of the paper also suggest that urban sprawl affects accessibility by HSR in a very negative way by lengthening travel times in the first and last miles. It is demonstrated that workers' commuting from sprawl areas to urban areas experience a longer commute in terms of time as well as mileage (García-Palomares, 2010; Sultana and Weber, 2007). In the case of HSR trips, in an ideal scenario, main origins and destinations could not vary with urban sprawl; however, suburbanisation usually involves people of medium/high income (main potential HSR users) and implies decentralisation of activities and creation of new business districts in the periphery of cities, suggesting a potential increase of total travel times. In fact, accessibility improvements derived from the construction of new HSR lines could be partially annulled if urban sprawl continues, supposing an important challenge for the potential development of HSR in so-called suburban nations (USA). In this sense, although the impacts of HSR stations' location for cities has been widely analysed in the literature, the consideration of central, edge and peripheral settings should be revisited, because not only the location of the station, but also its integration within urban transport systems could make a difference, as this paper has shown. In this sense, improving the level of intermodality of stations favouring the link between HSR and local transport systems would help to reduce total travel times.

Finally, the results obtained in dynamic analysis of access and egress travel times can feed mode choice models in order to analyse high-speed rail and air transport competition in a more realistic way. As demonstrated by Martin et al. (2014), the probability of choosing a plane or train changes spatially according to access and egress times to terminals. Future research will take advantage of new Big Data sources in order to analyse the influence of intra-urban spatiotemporal variations of access and egress travel times in modal choice.

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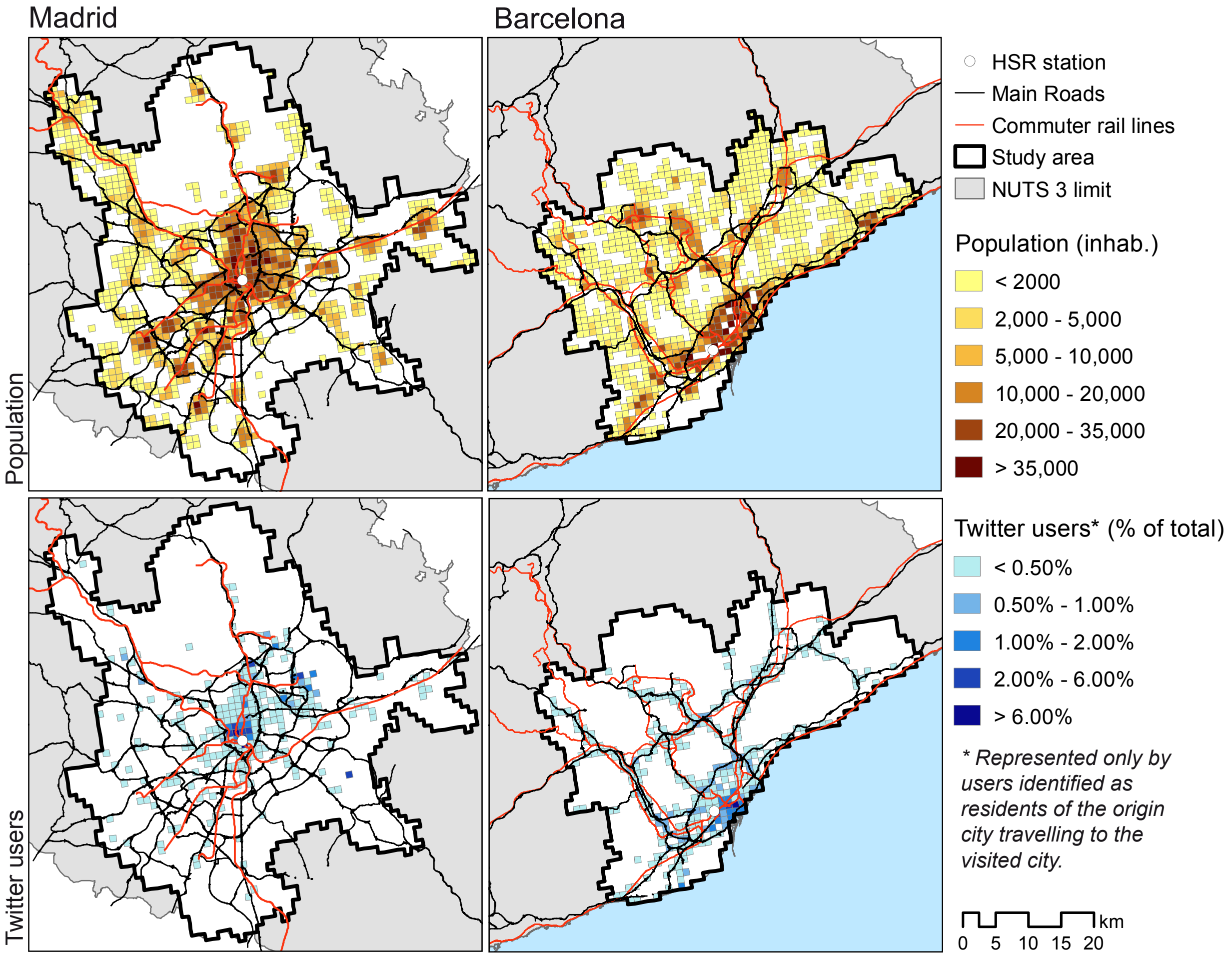
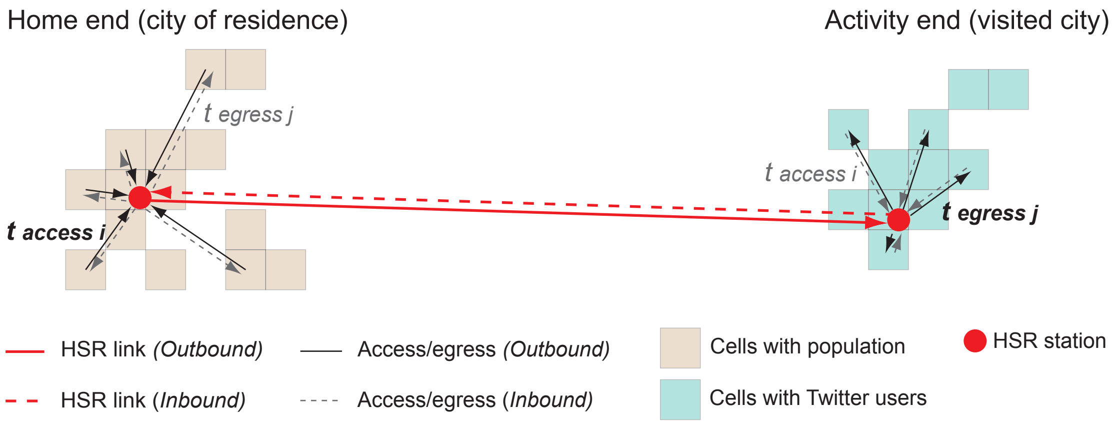


** Represented only by users identified as residents of the origin city travelling to the visited city.*



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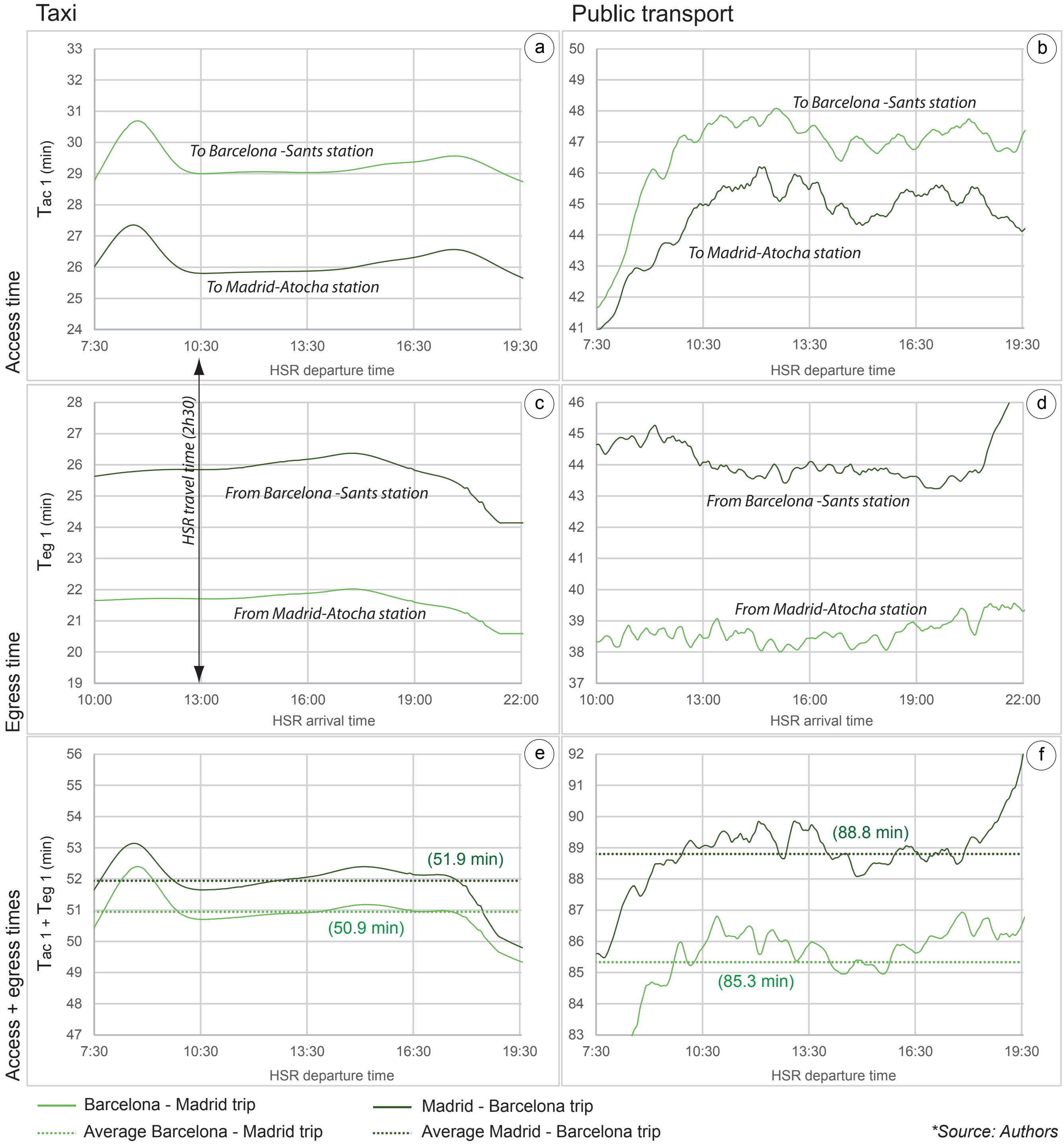

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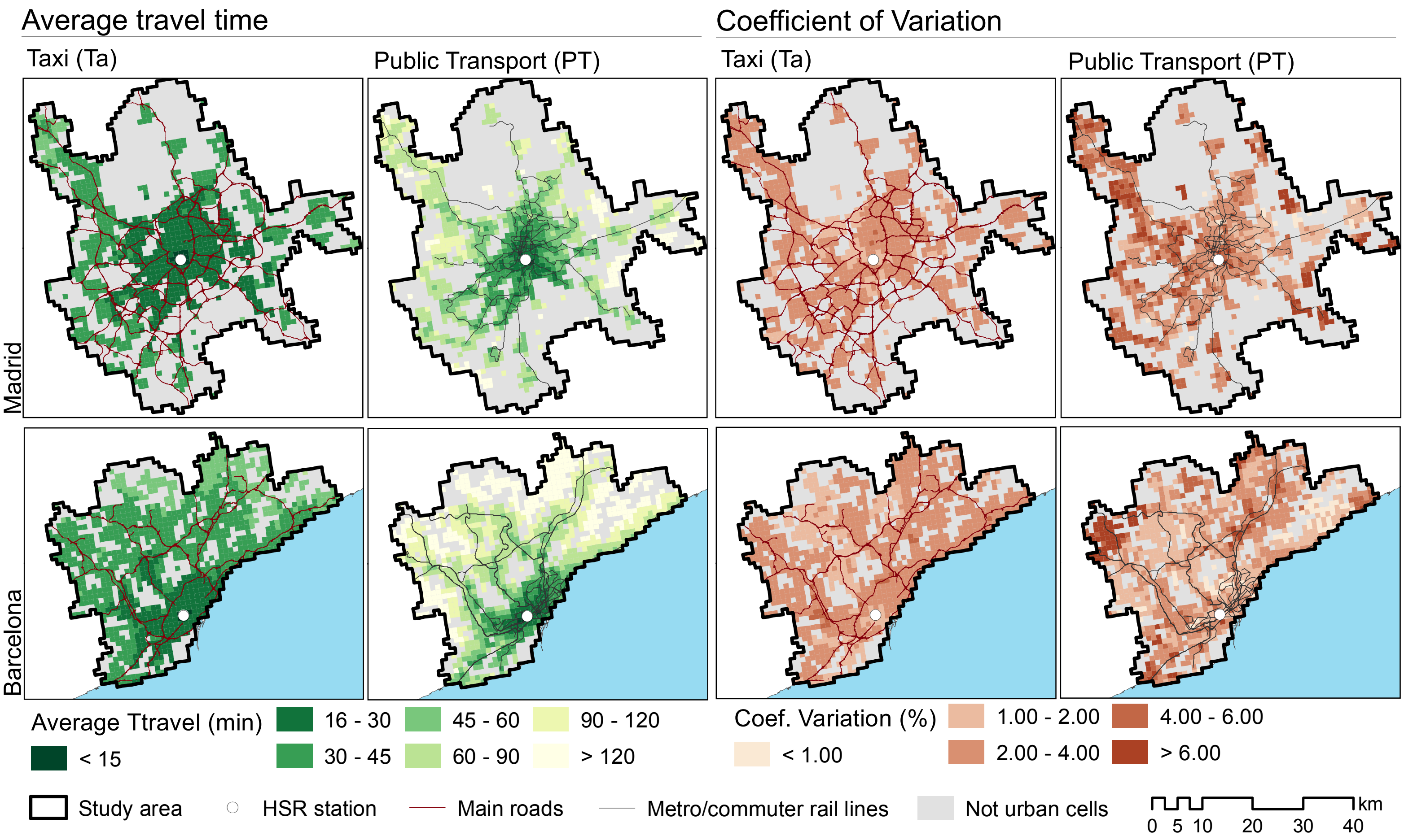
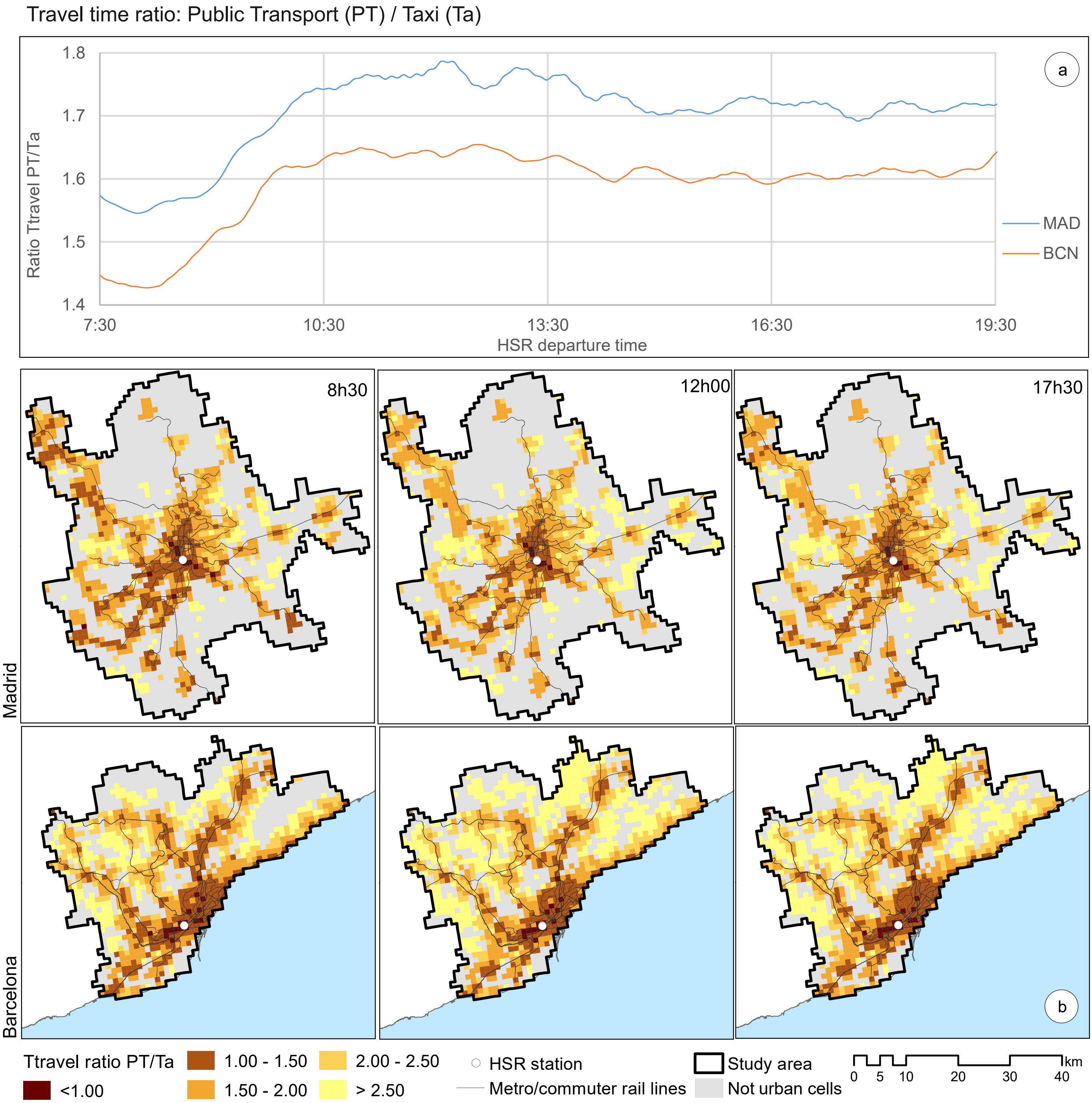

Average travel time
Coefficient of Variation
Taxi (Ta)
Public Transport (PT)
Taxi (Ta)
Public Transport (PT)
Madrid
Barcelona
Average Ttravel (min)
< 15
16 - 30
30 - 45
45 - 60
60 - 90
90 - 120
> 120
Coef. Variation (%)
< 1.00
1.00 - 2.00
2.00 - 4.00
4.00 - 6.00
> 6.00
Study area
HSR station
Main roads
Metro/commuter rail lines
Not urban cells
0 5 10 20 30 40 km


Travel time ratio: Public Transport (PT) / Taxi (Ta)
a
Ratio Ttravel PT/Ta
1.8
1.7
1.6
1.5
1.4
7:30
10:30
13:30
16:30
19:30
HSR departure time
MAD
BCN
8h30
12h00
17h30
Madrid
Barcelona
b
Ttravel ratio PT/Ta
<1.00
1.00 - 1.50
1.50 - 2.00
2.00 - 2.50
> 2.50
HSR station
Metro/commuter rail lines
Study area
Not urban cells
0
5
10
20
30
40
km