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DYNAMIC LOCATION-ALLOCATION MODELS FOR SHOPPING CENTERS: INTEGRATING TRANSPORT AND TRAFFIC DATA INTO THE NETWORK

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ABSTRACT

Location-allocation models are algorithms for finding the optimal location for services and facilities. Traditionally, these models were performed statically, without considering changes in network and service demand throughout the day. We evaluated the impact of incorporating the dynamic characteristics of public transport service networks and daily traffic behavior on covered demand. For this purpose, big data sources were used, drawing from Madrid's public transport data and TomTom's traffic history. Dynamic location-allocation models were developed using both data sources to incorporate the temporal and spatial details of public transportation frequencies and vehicular congestion. We found that daily variation in public transportation service and congestion affects the number of people who can visit a shopping center within a specified time frame. This research incorporates variables from new data sources, thereby enabling the development of dynamic models. This approach is helpful for decision-making related to the localization of services within cities.

Keywords: Location-allocation models; big data; dynamic; transport frequency; traffic.

MODELOS DINÁMICOS DE LOCALIZACIÓN Y ASIGNACIÓN DE CENTROS COMERCIALES: INTEGRACIÓN DE DATOS DE TRANSPORTE Y TRÁFICO EN LA RED

RESUMEN

Los modelos de localización-asignación son algoritmos utilizados para encontrar la ubicación óptima de servicios e instalaciones. Tradicionalmente, estos modelos se realizaban de forma estática sin tener en cuenta los cambios en la red y la demanda de servicios a lo largo del día. Nosotros evaluamos el impacto de incorporar las características dinámicas de las redes de servicios de transporte público y el comportamiento diario del tráfico en la demanda cubierta. Para ello, se utilizaron fuentes de big data, a partir de los datos de transporte público de Madrid y del histórico de tráfico de TomTom. Se desarrollaron modelos dinámicos de localización-asignación utilizando ambas fuentes de datos para incorporar los detalles temporales y espaciales de las frecuencias de transporte público y la congestión de vehículos. Descubrimos que la variación diaria del servicio de transporte público y de la congestión

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afecta al número de personas que pueden visitar un centro comercial en un periodo de tiempo determinado. Esta investigación incorpora variables procedentes de nuevas fuentes de datos, lo que permite desarrollar modelos dinámicos. Este enfoque es útil para la toma de decisiones relacionadas con la localización de servicios dentro de las ciudades.

Palabras clave: Modelos de localización-asignación; big data; dinamismo; frecuencia de transporte; tráfico.

1. Introduction

As one of the most dynamic metropolitan areas in Europe, Madrid plays a key role in the European Union's urban system. Madrid's location as Spain's political, economic, and cultural hub boosts its tourism and regional growth (García, 2021). The commercial sector is vital for the city's vibrancy. This includes shopping centers, retail corridors, and business districts. It shapes how people move, how land users use it, and how consumers behave (Arenas *et al.*, 2021).

Madrid is one of the top European cities for international tourists and economic activity. Its retail and business markets are key to local and regional competitiveness (Pagliara *et al.*, 2015). These commercial facilities are more than places to shop. They are also key factors that impact accessibility, transport needs, and service fairness in the metro area (Wang & Niu, 2019). It is important to study the layout of shopping centers. They also want to see how easily people can access them. This is especially true as we strive to develop urban planning that is more inclusive and centered on proximity.

With the evolution of modern lifestyles, the retail market has experienced remarkable changes, ranging from small independent stores to large shopping malls (Cheng *et al.* 2007). These facilities receive many customers and generate employment and revenue for various businesses within their facilities. In the metropolitan area of Madrid, there are a wide variety of shopping malls. The ease of access to such businesses is fundamental to ensuring that many people visit their stores and use their services. Strategic shopping mall location is crucial for attracting more customers. Therefore, accessibility by all modes of public and private transportation is a priority. Inadequate location selection can have long-term negative consequences that can lead to serious financial impact (Graig 1984). Choosing suitable locations significantly contributes to business success. In addition, it is essential to consider the presence of competitors in the area.

In this context, Serra & ReVelle (1994) explained that location-allocation models involving competing facilities include more than one company competing for a shared market; therefore, the location of a new facility affects not only its captured market share but also that of its competitor. The problem of locating facilities that share customers with competitors raises the possibility of competition. Thus, the new facility must compete with existing facilities in the market (Shan *et al.* 2019). The incorporation of other establishments affects the business share and profits of existing establishments (Lai *et al.* 2020).The location models of sales points in competition seek the best location for one or more new centers that compete to maximize the number of customers captured by competitors.

Few studies explicitly consider spatial competition in shopping mall location issues. Hotelling (1929) laid the groundwork for understanding duopoly competition. He introduced a linear model that assumes users go to the facility closest to them. The author suggests that consumers do not always pick the lowest-priced option. This challenges previous beliefs. Demand shifts slowly among competitors. This occurs due to factors such as location and personal preferences. He applies a basic mathematical model. This model demonstrates that steady consumer behavior yields a more stable price balance than past studies have indicated. This simplified framework laid the foundation for more complex probabilistic models such as Huff's gravity-based model (1964), which calculates the probability of a customer visiting a facility based on its attractiveness and its distance from the consumer. Subsequent studies refined these approaches by incorporating additional variables such as store size, parking availability, and perceived utility (Nakanishi & Cooper, 1974).

These competitive location models have been extended to various real-world applications, including the siting of clothing and furniture stores (Huff, 1964), shopping centers (Drezner *et al.*, 2002), and hotels (Drezner, 2010). Bell (1998) states that the study provides a broad framework for understanding how consumers choose stores. It examines fixed and variable shopping costs, the smallest basket size, and how loyalty, both general and category-specific, affects buying behavior. More recently, models that maximize shared market potential have been applied to retail contexts, including shopping malls (Ahmad *et al.*, 2017; Ahmadi & Ghezavati, 2020; Lai *et al.*, 2020), with varying success in identifying optimal trade-off points between access and exclusivity.

Ahmad *et al.* (2023) studied shopping mall locations in West Amman, Jordan. They used a temporal resilience framework with the Network Analyst tool in ArcGIS. This helped them assess travel times to each mall. The research indicates that the area has an excessive number of shopping malls. This is due to poor planning. As a result, there are too many stores for the number of people living in the area. The results suggest that using planning standards from other areas could improve the situation. This study opens the door for future research on how shopping center locations affect different areas. It provides valuable insights for urban planners and retail stakeholders (Dong *et al.*, 2023).

However, despite their theoretical robustness, most of these models rely on static assumptions about travel time and accessibility. Only a few studies, such as Banerjee *et al.* (2020), begin to incorporate temporal data—using GPS records to optimize bike-sharing station locations—but these are still rare in the context of shopping mall planning. This reveals a notable gap in the integration of dynamic transport network data, such as real-time congestion or scheduled public transport variation, into location-allocation models for commercial facilities. Addressing this gap is one of the main motivations of the present study.

It is important to highlight that so far in the literature review, little research has been found on the location of shopping centers in which Big Data sources have been used to analyze the dynamism of transport networks. Therefore, the aim of this study is to analyze the effect of the dynamic component of the public transport network and congestion on the demand served during the day by the current shopping centers in Madrid. To achieve this, we used two complementary Big Data sources. The first is the General Transit Feed Specification (GTFS). It is a standard format that machines can read. GTFS provides detailed information about public transportation schedules, stop locations, and transit routes. Many use it to model multimodal transit access. The second source is historical traffic data from TomTom. This company provides real-time and archived traffic info. They gather data from millions of GPS devices. This data shows congestion levels and average travel speeds on the road network.

Using the GTFS data, we constructed a public transportation network to simulate population movement to commercial facilities and services by bus, metro, and other modes. With TomTom data, we modeled private vehicle movement across the urban road network, incorporating the spatial and temporal variation in congestion patterns observed throughout the day.

Recently, GTFS (General Transit Feed Specification) data has become common in transport geography. It helps model public transport accessibility. GTFS gives standard info about transit routes, stops, schedules, and frequencies. This info helps with detailed time analyses. Researchers such as Farber *et al.* (2014), Stępniak & Goliszek (2017), and Karner (2018) have demonstrated that GTFS-based models effectively highlight accessibility inequalities by simulating travel times at various times throughout the day. These studies employed metrics such as the Gini index and standard deviation. They measured accessibility among social groups and urban areas. Other applications, such as those by Liu *et al.* (2023, 2024) and Braga *et al.* (2023), highlight the importance of incorporating variability in public transport services to more accurately assess accessibility, particularly for vulnerable populations or during system disruptions.

Despite these advances, most GTFS-based studies have focused on accessibility measurement rather than facility location. Kotavaara (2018) is one of the few exceptions, using GTFS data to identify optimal locations for healthcare services in Finland. GTFS is rarely used in retail location-allocation models. This presents an opportunity to apply this method to commercial planning.

Simultaneously, TomTom data has emerged as a vital resource for modeling vehicular mobility and congestion patterns. TomTom uses GPS data from millions of vehicles. This helps create historical traffic profiles. These profiles show average speeds, travel times, and congestion levels. They provide insights over time and in different areas. Research conducted by Moya-Gómez & García-Palomares (2017), García-Palomares *et al.* (2018), and Dingil *et al.* (2018) has employed TomTom data to evaluate the dynamics of car accessibility, simulate traffic conditions, and benchmark transport performance across urban landscapes.

Additionally, Pritchard *et al.* (2019) and Tanveer *et al.* (2020) have integrated TomTom data with General Transit Feed Specification (GTFS) data to investigate multimodal accessibility. TomTom data is effective for assessing the performance of transportation systems. However, its application to location-allocation problems in commercial facilities is still in its early stages. Recent work, including that of Moyano *et al.* (2018) and Moya-Gómez *et al.* (2024), demonstrates how incorporating congestion data enhances the realism of spatial planning models. These initiatives highlight the significance of considering time-dependent travel patterns, particularly when delineating retail service areas within congested urban environments.

Nevertheless, further research is needed to understand the implications of these patterns on consumer behavior and facility performance. This study addresses the gap by using TomTom traffic profiles. It assesses the ease of access to shopping centers in the Madrid metropolitan area. Building on this literature, our study proposes a novel integration of GTFS and TomTom data into a dynamic location-allocation model for shopping centers in the Madrid metropolitan area. By considering temporal variability in both public and private transport networks, we aim to evaluate how accessibility patterns evolve throughout the day and how they influence the potential demand captured by existing commercial facilities. The study is guided by the following research questions:

• How do fluctuations in public transport frequency and road congestion throughout the day affect accessibility to shopping centers?

• To what extent do these dynamic accessibility patterns influence the demand coverage and market share under competitive conditions?

To explore these questions, we used two dynamic spatial optimization strategies. The maximize attendance model demonstrated how changes in public transportation and road congestion impact demand at shopping centers during the day. The maximize shared market model looked at competition. It demonstrated how demand is spread across current facilities.

The following structure organizes the paper. First, Section 2 presents the research method undertaken in this study. Section 3 shows our results from the dynamic location-allocation model for shopping centers in Madrid. In Section 4, we present our findings and conclude the paper by summarizing our main conclusions.

2. Materials and methods

2.1. Study Area

To conduct this research, Madrid was chosen as the scenario for the empirical application of location-allocation models. The researchers selected Madrid because of data available to develop the location-allocation models. In addition, Madrid stands out as a dynamic city, with a metropolitan area abundant in different services and facilities. It is a multicultural city that offers a conducive environment for the location of services and businesses. The Madrid metropolitan area is located in central Spain and is part of the Community of Madrid, the country's capital city. Various global classifications and rankings reflect the importance of the Madrid metropolitan area. According to the Global Power Cities Index 2019, which ranks 48 cities in the world by their magnetism in attracting people, capital, and businesses, Madrid is the thirteenth city in the world and the fifth in Europe, ranking leading London, New York, Tokyo, and Paris. The metropolitan area of Madrid has the largest population and provides services in Spain. It includes 28 municipalities (Figure 1) in which approximately 6,780,000 inhabitants live according to the 2020 Population Register. It is the main metropolitan area in Spain, surpassing Barcelona, where 5.5 million people live (Ayuntamiento de Madrid 2020).

The main communication infrastructures in the metropolis have converged, positioning it as the primary logistics hub in Spain and Southern Europe. There is a significant network of highways and roads, including both radial and ring roads. It forms the core of national railway transport and facilitates effective connections with other autonomous communities and Europe.

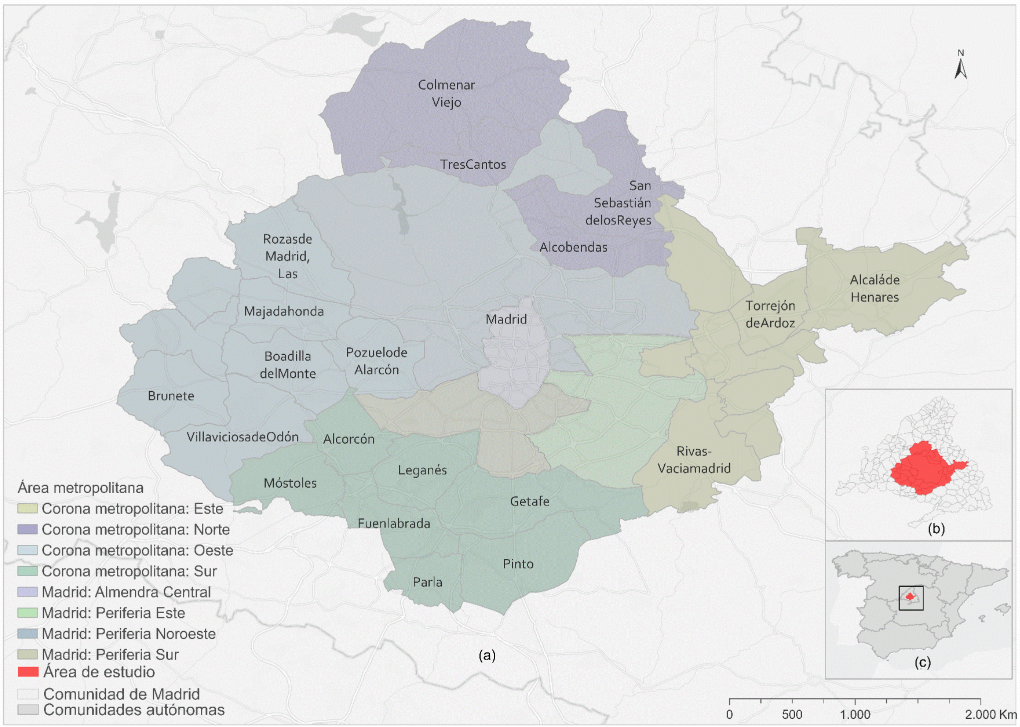


Figure 1. Study area. (a) Metropolitan area; (b) Community of Madrid; (c) Spain.

2.2. Data for location-allocation models

2.2.1. Public transportation networks and TomTom traffic history

The dynamic component was incorporated into the street network downloaded from the National Geographic Information Center in Shapefile format. The GTFS files were acquired from the Madrid Regional Transport Consortium (CRTM) data portal. Using these data, a network was constructed to simulate the population movement by public transportation (Figures 2-3). For the design of Location-Allocation Models (LAM) incorporating dynamism into the public transportation network. This network was built using the DisplayGTFS, AddGTFS, and Network Analyst tools in ArcMap 10.6 software from ESRI (Environmental Systems Research Institute).

Additionally, historical traffic profiles (the Historical Speed Profiles product) collected by TomTom were used in the design of the network that simulates private car travel (Figures 4-5).

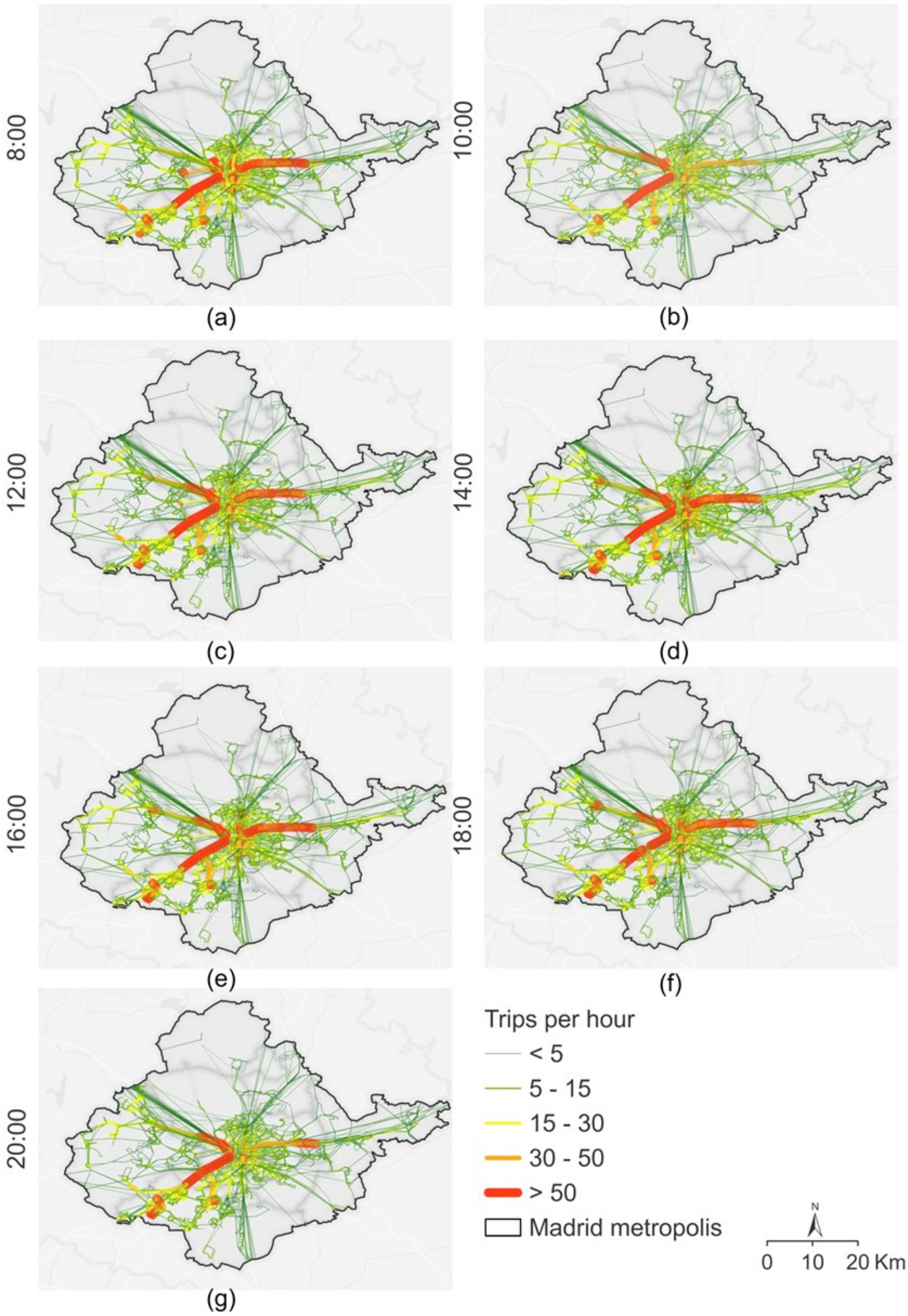


Figure 2. Public transportation travel frequencies on Thursdays. Frequencies at (a) 8:00 h; (b) 10:00 h; (c) 12:00 h; (d) 14:00 h; (e) 16:00 h; (f) 18:00 h; (g) 20:00 h.

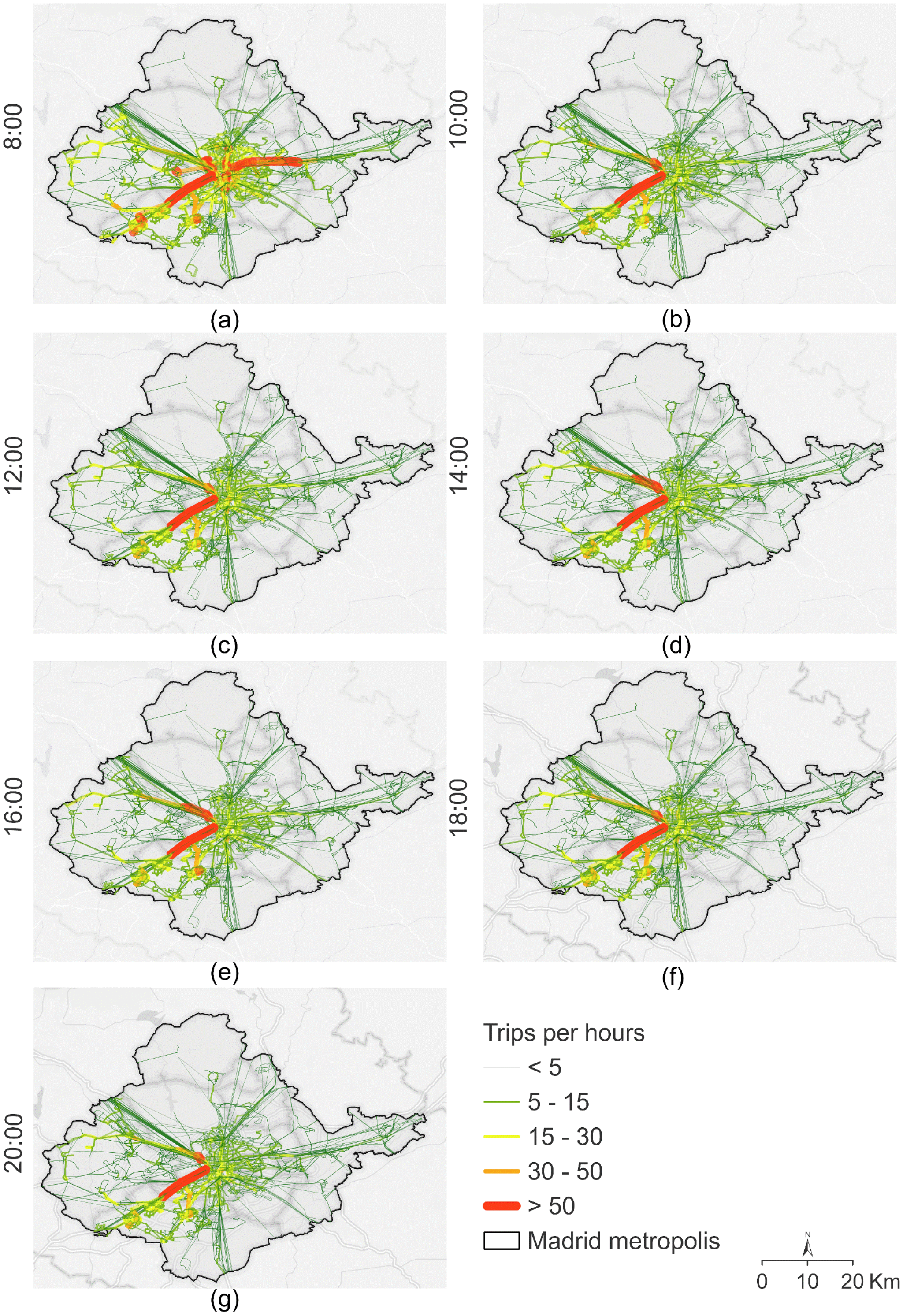


Figure 3. Public transportation travel frequencies on Saturdays. Frequencies at (a) 8:00 h; (b) 10:00 h; (c) 12:00 h; (d) 14:00 h; (e) 16:00 h; (f) 18:00 h; (g) 20:00 h.

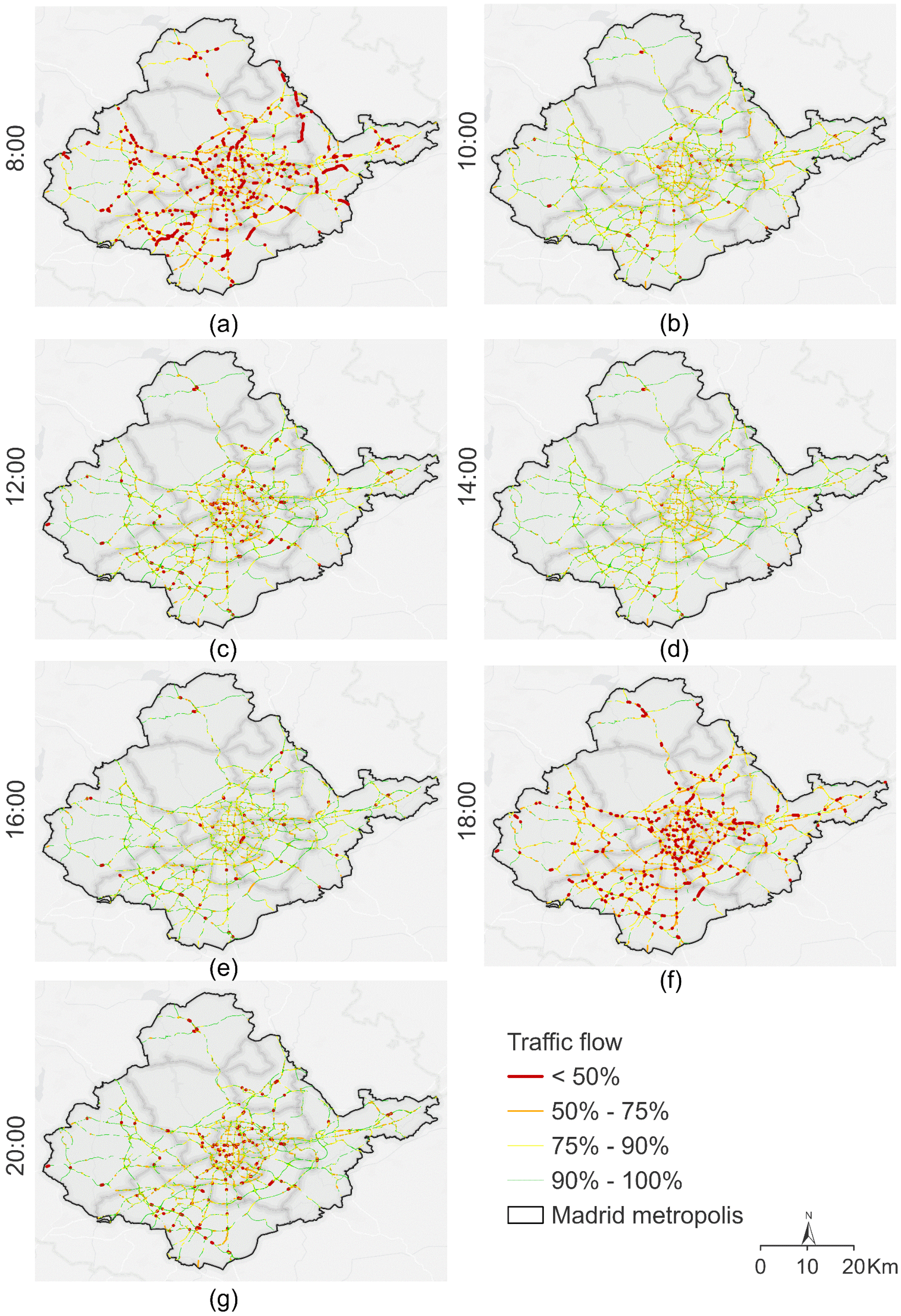


Figure 4. Thursday traffic behavior based on TomTom data. Traffic at (a) 8:00 h; (b) 10:00 h; (c) 12:00 h; (d) 14:00 h; (e) 16:00 h; (f) 18:00 h; (g) 20:00 h.

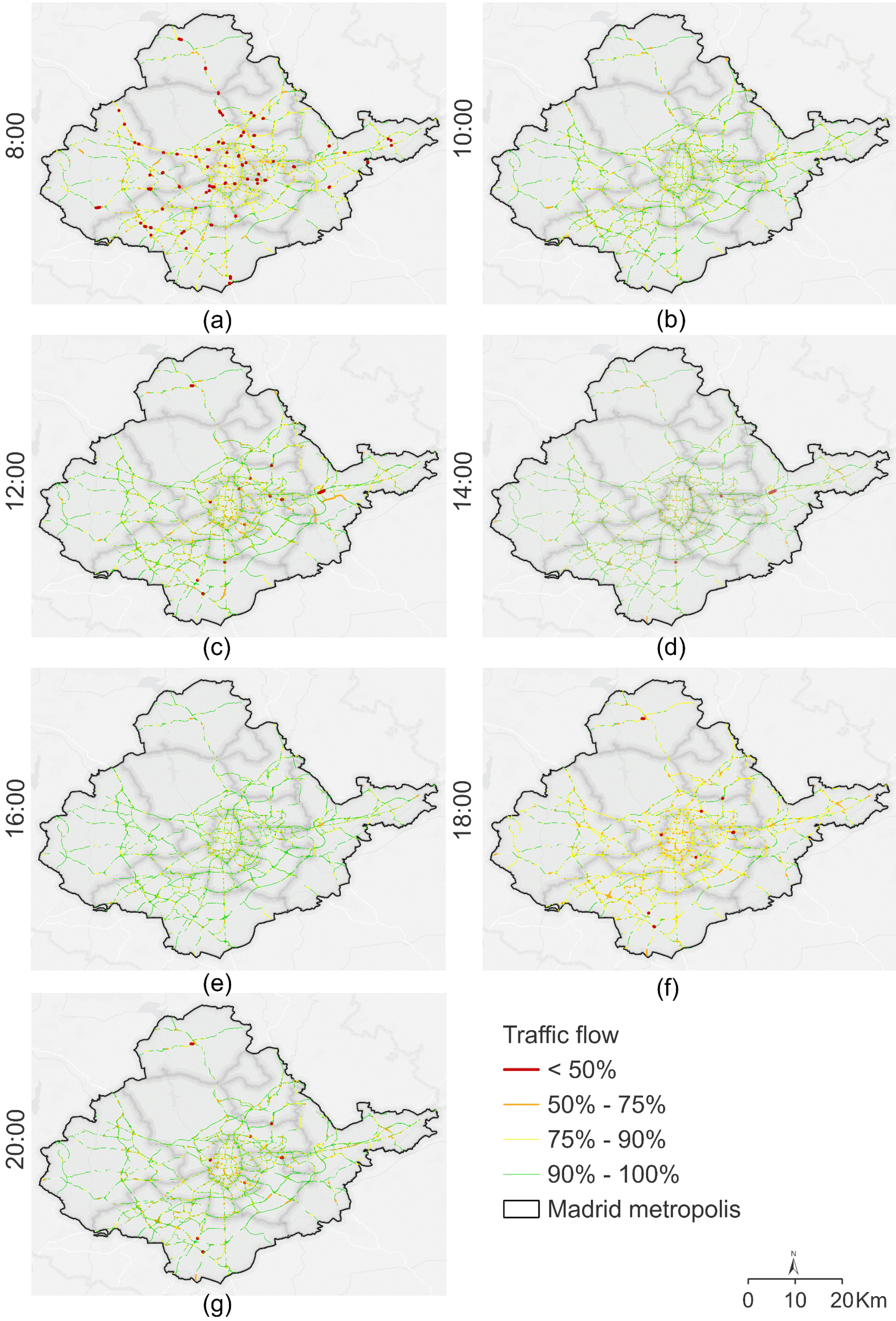


Figure 5. Saturday traffic behavior based on TomTom data. Traffic at (a) 8:00 h; (b) 10:00 h; (c) 12:00 h; (d) 14:00 h; (e) 16:00 h; (f) 18:00 h; (g) 20:00 h.

Based on the two products managed by TomTom (MultiNet® and Historical Speed Profile), the private transportation network used to calculate LAM with a dynamic component during the day is constructed. The established parameters are arc connections through endpoints, prohibited turns, traffic directions, and section hierarchy.

The following impedances are defined:

• Average travel time (times with average speeds),
• Kilometers (length of network arcs),
• Minutes (times obtained using the speeds calculated in the MultiNet product), and
• Travel Time (variation of arc speeds).

Both networks were used to execute the location-allocation model (LAM), allowing for the analysis of the mobility patterns of demand by day and hour.

2.2.2. Census Tracks and Shopping Centers

To execute LAM, census data at the census section level downloaded from the Continuous Population Register of 2020 and available on the Spanish National Institute of Statistics (INE) server were used. The cartography of the census sections downloaded from the Madrid Community data server was used to georeferencing the population data. Subsequently, the centroid of each census section was calculated and used as the demand point for the service. In the location models, a layer with the coordinates of the shopping centers was employed as the supply point. Both layers were downloaded in Shapefile format from the Madrid Community open data portal. We worked with 91 centers located in the metropolitan area of Madrid. This file contains geographic coordinates, shopping center names, and gross leasable areas.

2.3. Methods

In the introduction, this article discusses various theoretical and practical approaches to developing location-allocation models (LAM). These approaches have resulted in diverse solutions, including maximizing attention and maximizing market share in terms of time or distance for the target population. However, most location-allocation models to date have not considered the temporal dynamism of the transport network used for model development. This oversight stems from difficulties in obtaining high temporal-resolution data, which is a limitation that has been fortunately overcome with the advent of big data sources.

In this context, this study considers the incorporation of dynamism in the network input to LAM. With the emergence of new data sources, such as big data, researchers have investigated the implementation of LAM at different times on Thursdays and Saturdays. Using data from both public and private transportation networks, this study analyzed the impact of bus and private car travel on demand throughout the day.

2.3.1. Selection of Candidates and Demand

Current shopping centers in the metropolitan area of Madrid were used as required facilities, and their gross leasable area (GLA) was used as an attraction parameter. Meanwhile, demand points were obtained from centroids corresponding to census sections. The Features to Point tool in ArcGIS Pro 3.2 extracted centroids in census sections. These sections include a field containing the population used to weigh the demand.

2.3.2. Development of dynamic location-allocation model

After establishing public and private transportation networks and identifying candidate and demand sites, we implemented location-allocation models using the location-allocation module of ArcMap 10.6 (ESRI) Network Analyst. This study analyses the impact of changes in public transportation frequencies and congestion on the demand served by existing shopping centers in the Madrid metropolitan area. This study implemented solutions that maximize assistance and maximize market share.

A) Maximize Attendance solution

Existing shopping centers in the Madrid metropolitan area served as required facilities, with their gross leasable area (GLA) as a critical attraction parameter. Demand points were derived from the respective centroids of the census tracts, each containing the population data used to gauge demand. A travel time threshold of 10 minutes from demand points to candidate sites was applied to define service areas. This value is grounded in the empirical findings of Gutiérrez Puebla & Chicharro Fernández (2003), who reported an average access time of 11 minutes to selected shopping centers in the Madrid metropolitan area. Additionally, using a 10-minute travel time threshold is a well-established method in facility location planning. It ensures that facilities are optimally positioned to efficiently serve demand points, thereby enhancing accessibility and service coverage. This approach is widely supported by optimization models and practical applications in urban service planning, demonstrating its effectiveness in improving spatial coverage and minimizing response times (Yildiz & Ekinci, 2017). The maximize attendance strategy prioritizes facilities by assigning maximum demand weight, assuming that demand decreases with distance from candidate sites to potential demand points. According to Alonso (2016), demand is maximized within a certain distance threshold, emphasizing proximity to supply points. Maximizing attendance suggests that the further people travel to access a facility, the less likely they are to use it (Erfani *et al.* 2018, Rahman *et al.* 2021). The equation used is as follows: (Zhang *et al.* 2024).

$$Maximizar\ Z = \sum_{i=1}^{m} \sum_{j=i}^{n} p_i \left(S - d_{ij}\right) x_{ij}$$

Where $i =$ set of demand locations; $j =$ set of candidate locations; $p_i =$ population to be served at the demand site i; $S =$ distance; $d_{ij} =$ the shortest distance from a site i *to* site *j;* $x_{ij} =$ decision variable that will take the value of 1 if the demand i is covered by the candidate site j and 0 otherwise.

We applied the maximize attendance strategy on two specific days (Thursday and Saturday) across various time slots: 8:00 h, 10:00 h, 12:00 h, 14:00 h, 16:00 h, 18:00 h, and 20:00 h, chosen to represent typical weekdays and weekends. Additionally, we examined off-peak hours (10:00 h, 12:00 h, 14:00 h, 16:00 h, 20:00 h) to assess network behavior when public transportation frequencies and road congestion are low. This hour allowed us to evaluate the impact of different transportation frequencies and congestion on shopping center attendance throughout the day.

B) Maximize market Share solution

Maximizing market share solution is commonly used to identify facilities where competitor characteristics must be considered (Banerjee *et al.* 2020, Drezner 2011) In this case, the maximize market share solution is used, maintaining parameters similar to those of the previous model but adjusting the gross leasable area of each shopping center as the attraction criterion.

The equation used is as follows:

$$Maximizar\ Z = \sum_{i=1}^{m} a_i y_i + \sum_{i=1}^{m} \left(\frac{a_i}{2}\right) z_i$$

Subject to:

$$y_i \leq \sum_{j \in N_i} x_j \qquad i = \{1,2,\dots,m\}; j = \{1,2,\dots,n\} \qquad (1)$$

$$z_i \leq \sum_{k \in K_i} x_k \qquad i = \{1,2,\dots,m\} \qquad (2)$$

$$z_{i+}y_i \leq 1 \qquad i = \{1,2, \dots, m\} \qquad (3)$$

$$\sum_{j \in J_0 \cup J_N} x_{j=P} \qquad (4)$$

Where i = demand sites that are available for capture; j = candidate sites for facilities; J_0 = set of occupied facilities; J_N = set of non-occupied facilities and are eligible; a_i = population in node i; y_i = {1 if node i gets a new service within S_i that is closer to 1, 0 otherwise; x_j 1 if the facility is located in j, N_i = $\{j \in J_N \mid d_{ij} < S_i \}$ set of facilities that are strictly closer to node i than to its nearest facility; d_{ij} = shortest distance between site i and site j; S_i = distance from node i to the nearest site j; K_i = the set of occupied and unoccupied facilities located at the same distance from i as the nearest facility i; z_i= {1 if node i es captured by a service located within K_i; 0 otherwise.

If node i is captured by a facility located within k_i, meaning the facility currently closest to i or a facility whose distance from i is equal to the distance from i to the currently closest facility, then z is 1 if it is captured and doubly equipped.

Constraints (1) form the basis of the formulation. They state that a demand point is not captured by a new facility unless the facility is located closer to i than its currently closest facility. Constraints (2) indicate that a demand node i is captured but doubly served $z = 1$ only if a new facility is located in a position $k \in K$, the set of positions, equally distant from i as the currently closest provider to node i. Constraints (3) prevents a demand site from being captured in more than one location. Constraints (4) limit the number of new facilities. This is expressed as follows: if the travel cost from the demand point to the site of the incoming competitor is less than the current cost, the new competing establishment captures the demand. If the travel cost is the same, the demand is shared between the two (the new and the preexisting establishment). Finally, if the travel cost of the nearest site to the incoming competitor exceeds the travel cost of the competitor, the competitor does not capture the demand (Bosque *et al.* 2012). The model described in this section has been applied by various authors to locate retail sites (Saidani *et al.* 2012, Suárez-Vega *et al.* 2012), shopping centers (Ahmad *et al.* 2017), and bike stations (Banerjee *et al.* 2020), among others.

3. Results

This section summarizes the LAM results for shopping centers in Madrid's metropolitan area. First, the results obtained when applying the solution to maximize attendance are presented.Then, the outcomes derived from the solution to maximize market share are shown.

3.1. Demand Covered by the Solution Maximize Attendance

Table 1 lists the demand covered by the network of shopping centers in the metropolitan area of Madrid across various time slots using the GTFS public transportation network. It was observed that the allocated population barely reached 5 % on Thursdays and Saturdays within a 10 min travel time. The data indicate that shopping centers are not covered by public transportation because nearly 95 % of the population still needs to be allocated to any shopping center. The results show minimal differences between the studied days and time slots. To explain the changes in the covered population across time slots (Table 1), we utilized the 18:00 h time slot as a reference for comparison. We selected this time slot based on Google Maps graphs showing peak visiting hours at shopping centers. Analyzing Thursdays, a slight decrease was noted across most time slots, with the lowest value at 14:00 h representing 1.8 %. Conversely, Saturdays increased in some time slots, with the highest value again at 14:00 h (1.3 %).

Table 1. Population covered by shopping centers according to GTFS.

Hours	Thursday 10 min				Saturdays 10 min			
	Total	%	Inc.	Inc%	Total	%	Inc.	Inc%
8:00	296 797	5.1	3185	1.1	276 739	4.8	-6305	-2.2
10:00	292 228	5.1	-1385	-0.5	282 897	4.9	-147	-0.1
12:00	293 645	5.1	32	0.0	280 014	4.8	-3031	-1.1
14:00	288 254	5.0	-5358	-1.8	286 619	5.0	3575	1.3
16:00	290 517	5.0	-3096	-1.1	286 474	5.0	3429	1.2
18:00*	**293 613**	**5.1**	**0.000**	**0.0**	**283 044**	**4.9**	**0.000**	**0.0**
20:00	291 766	5.0	-1847	-0.6	284 812	4.9	1767	0.6

*Reference hour. Inc = Increment. min = minutes.

The low values in the allocated population and the minor differences in the data may be related to the distance of shopping centers from the main public transportation routes and the frequent disconnects between the centers and the urban fabric (Gutiérrez Puebla & Chicharro Fernández, 2003).

Error! No s'ha trobat l'origen de la referència. depicts the demand distribution profiles on T hursdays and Saturdays across different time slots using the GTFS network. The horizontal axis represents the various studied time slots, whereas the vertical axis indicates the population assigned to shopping centers. It is inferred that on Thursdays, there is greater demand for coverage in the early hours of the day (reflecting a higher public transportation frequency, although shopping centers are closed at 8:00). Coverage then declines at 10:00, recovering at 12:00 and 18:00, coinciding with popular shopping hours. On Saturdays, coverage is lower in the early hours (due to lower public transportation frequency), with the highest values at 14:00, 16:00, and 18:00. These hours correspond to when the Madrid population typically visits shopping centers on weekends. Overall, when using public transportation (GTFS), Thursdays witness a higher population allocation to shopping centers than Saturdays.

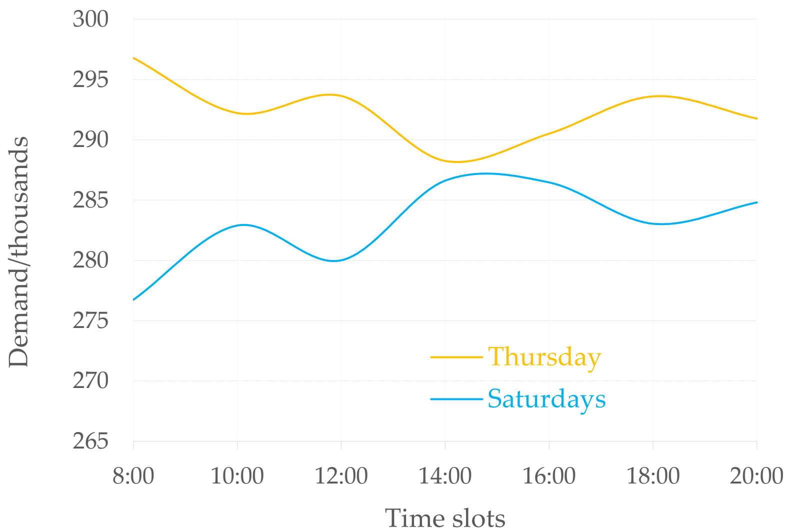


Figure 6. Population covered by shopping centers according to GTFS network.

Exploring the results obtained using TomTom (Table 2), it is observed that the covered demand on Thursdays and Saturdays exceeds 40 % across all studied hours. On Thursdays, at 14:00, shopping centers cover 45.2 % of the population. This higher percentage was associated with lower congestion during this hour. On Saturdays, the best coverage is at 8:00, with approximately 50 % of the population allocated.

The weekend results were due to reduced traffic congestion during the early hours on Saturdays. Moreover, the average percentage of the allocated population on Thursdays was 43.5 %, whereas on Saturdays, the average was 47.1 %. Comparing the averages for both days shows that Saturdays attract 3.6 % more people (211 860 customers).

Table 2. Population covered by shopping centers according to TomTom.

Hours	Thursday 10 min				Saturdays 10 min			
	Total	%	*Inc.	Inc%	Total	%	Inc.	Inc%
8:00	2 545 710	44.0	187 903	8.0	2 854 740	49.4	147 822	5.5
10:00	2 561 573	44.3	203 766	8.6	2 792 994	48.3	86 076	3.2
12:00	2 511 807	43.5	154 000	6.5	2 723 667	47.1	16 749	0.6
14:00	2 609 816	45.2	252 008	10.7	2 768 109	47.9	61 192	2.3
16:00	2 607 240	45.1	249 432	10.6	2 826 189	48.9	119 271	4.4
18:00	**2 357 807**	**40.8**	**0.000**	**0.0**	**2 706 918**	**46.8**	**0.000**	0.0
20:00	2 508 156	43.4	150 349	6.4	2 693 500	46.6	-13 418	-0.5

To compare the evolution of population coverage throughout the day (Table 2), the 18:00 time slot was selected as the reference value. It is observed that on Thursdays, 14:00 and 16:00, the most significant increases in the allocated population (10.7 % and 10.6 %, respectively). Focusing on Saturday data, a more significant percentage increase (5.5 % in the allocated population) occurred at 8:00. Additionally, the 16:00 h record a 4 % increase in coverage, an afternoon time when people frequently visit shopping centers on weekends.

Figure 7 illustrates the population profiles assigned on Thursdays and Saturdays across different time slots using the TomTom network.

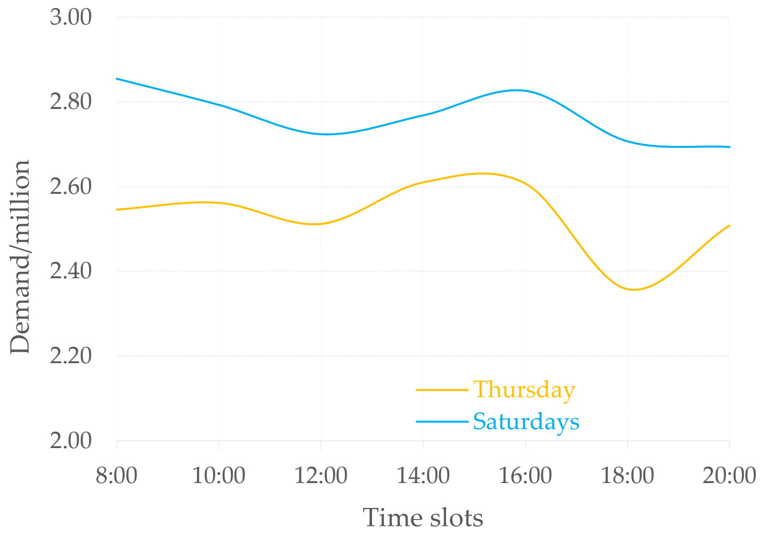


Figure 7. Population covered by shopping centers according to TomTom network.

Saturdays exhibit higher coverage than Thursdays. On Saturdays, the highest population coverage occurs at 8:00 and 16:00; at 18:00, congestion increases, resulting in a decrease in the population allocated to shopping centers within that 10 min time slot. Conversely, notable values were observed on Thursdays at 14:00 and 16:00 (**Error! No s'ha trobat l'origen de la referència.**), indicating lower v ehicle traffic during these time slots. Meanwhile, a decrease was evident at 18:00, a time of significant traffic volume in Madrid, according to TomTom traffic data. Significant differences in population coverage were observed between GTFS and TomTom. Note that with public transportation, the weekend coverage of demand is lower. With the TomTom network, the opposite occurs, as Saturdays experience less vehicular congestion, leading to increased demand compared with Thursdays (**Error! No és una autoreferència de marcador vàlida.**). Furthermore, the population can leverage the low vehicular congestion on weekends, especially at 14:00 and 16:00, to visit shopping centers for shopping or dining.

Table 3. Differences in the population covered between Saturday and Thursday (Saturday-Thursday).

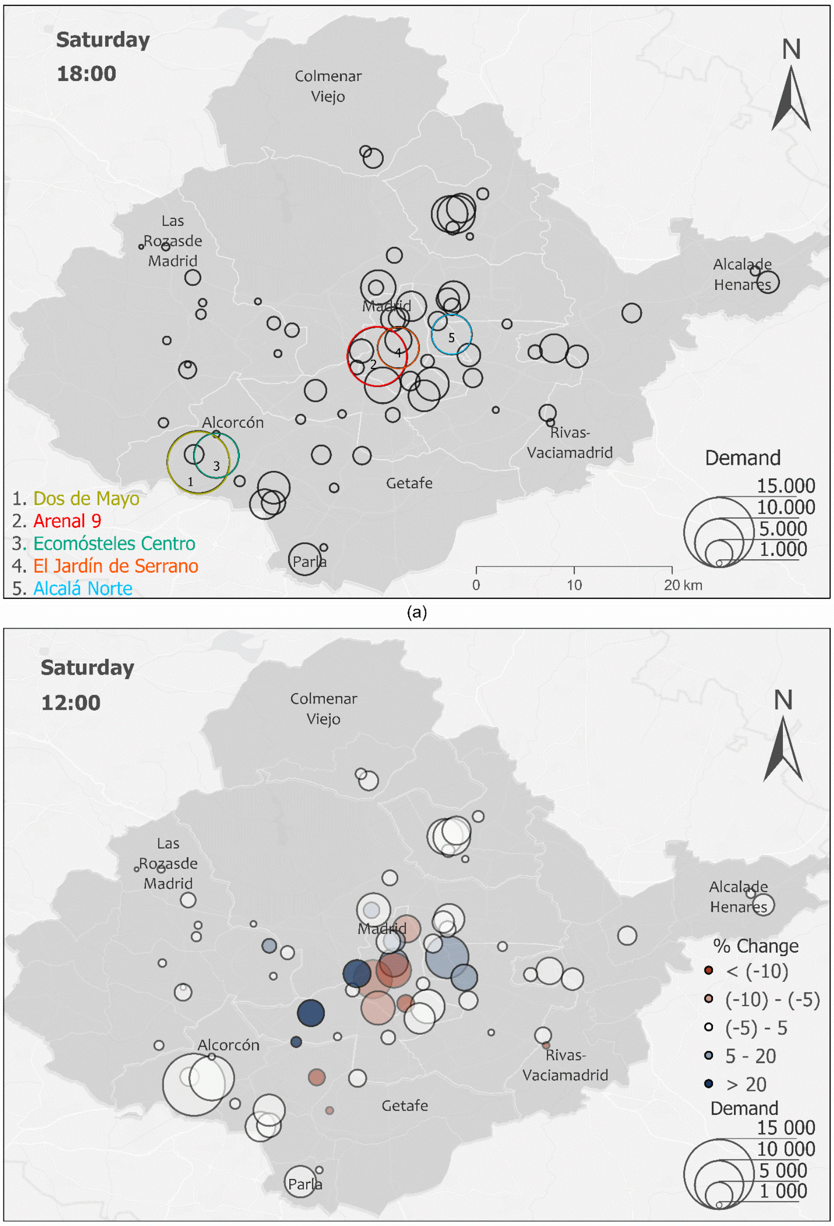
Hours	GTFS		TomTom	
	Total	%	Total	%
8:00	-20 058	-6.8	309 030	12.1
10:00	-9 331	-3.2	231 421	9.0
12:00	-13 631	-4.6	211 860	8.4
14:00	-1 635	-0.6	158 294	6.1
16:00	-4 043	-1.4	218 949	8.4
18:00	**-10 568**	**-3.6**	**349 111**	**14.8**
20:00	-6 954	-2.4	185 344	7.4

Maps (Figure 1) depict the population coverage results by shopping centers across different time slots and their percentage changes. These percentages are derived by comparing the demand during the 18:00 time slot and analyzing the percentage increase or decrease in hourly allocations on Thursdays and Saturdays using both networks.

For improved visualization, only 18:00 h and 12:00 h on Saturdays were considered. The size of the circles indicates the population assigned to each shopping center at 18:00 h , while red tones indicate changes between 12:00 h and 18:00 h.

Figure 1 reveals that when using the GTFS network, most shopping centers exhibit changes compared with the reference hour (18:00 h). The 18:00 h time slot showcases some shopping centers with significant population volumes, such as Dos de Mayo, Arenal 9, El Jardín de Serrano. On Saturdays, at noon, many shopping centers experience losses in captured demand compared with 18:00 h, especially those located in the peripheral and downtown areas of the metropolitan area. Examples of shopping centers affected by variations in public transportation frequency at noon include Ecomóstoles Centro, Arenal 9, and El Jardín de Serrano.

On Saturdays, shopping centers that achieve higher population allocation are Dos de Mayo, Arenal 9, Ecomóstoles Centro, El Jardín de Serrano, and Alcalá Norte. This behavior may be related to good connectivity with public transportation (higher frequency of trips and routes) between demand locations and shopping centers.



(b)

Figure 1. Population covered and percentage change between 12:00 h and 18:00 h h (GTFS). (a) Saturday at 18:00 h; (b) Saturday at 12:00 h.

The demand behavior of private transportation (TomTom network) was also analyzed, again using the 18:00 h time slot as a reference, to study the percentage change in covered demand during other time slots. Figure 2 shows that on Saturdays, at noon, many shopping centers record favorable percentage variations. These percentages stem from a higher allocated population on weekends and during times when people visit shopping centers more frequently. Moreover, the positioning of shopping centers, typically outside central areas, renders them more susceptible to weekday traffic congestion during the afternoon peak hours.

Regarding covered demand, the most favored shopping centers in both time slots are Los Ángeles, Plaza Aluche, Alcampo-Moratalaz, La Ermita, and Plaza Río (Figure 2). These commercial centers are situated adjacent to densely populated districts, including Arganzuela, Usera, Retiro, Moratalaz, Villaverde, and Carabanchel. Note that these shopping centers, with a higher allocated population, exhibit the following characteristics: they are located in the periphery of the Central Almendra of the

Municipality of Madrid, close to the M30 highway, and distant from areas of high traffic congestion in the Centro and Salamanca districts. These characteristics may be related to the extensive coverage of these shopping centers on Saturdays at 18:00 h, which coincides with a time when a considerable portion of the population visits Madrid shopping centers.

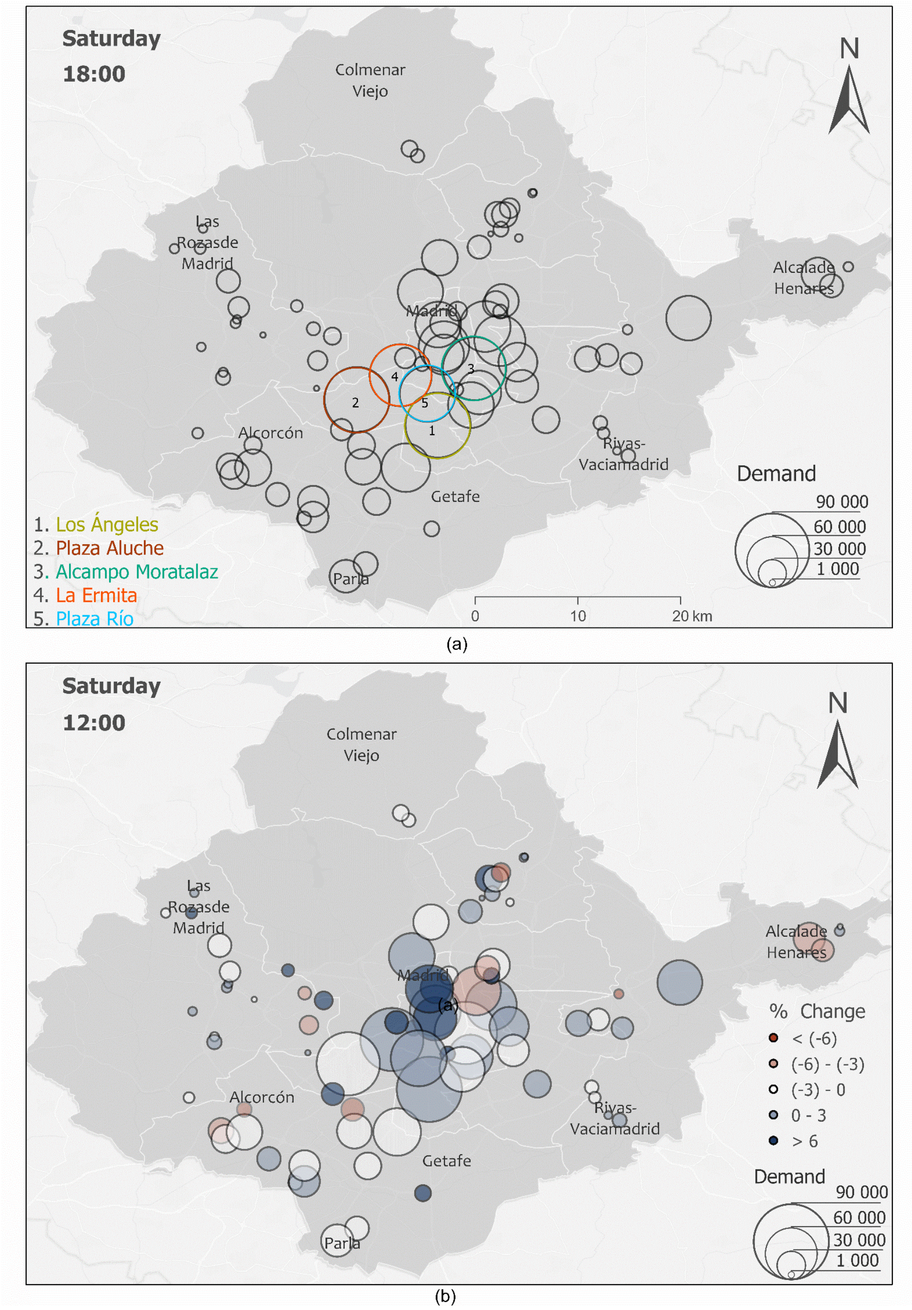


Figure 2. Population covered and percentage change between 12:00 h and 18:00 h (TomTom). (a) Saturday at 18:00 h; (b) Saturday at 12:00 h.

Figure 3 presents the average demand per day, hour, and network. Comparing GTFS with TomTom, differences in average population coverage among shopping centers were evident. For instance, regarding public transportation, a higher proportion of people traveled on Thursdays than on Saturdays, although the average demand remained similar across all time slots. Conversely, with TomTom, the opposite occurs, as Saturdays allocate more population than Thursdays, covering an average of almost 30 000 inhabitants at different times. Comparing the results obtained using both networks, we find that the average population allocated to shopping centers was significantly more likely to use private transportation.

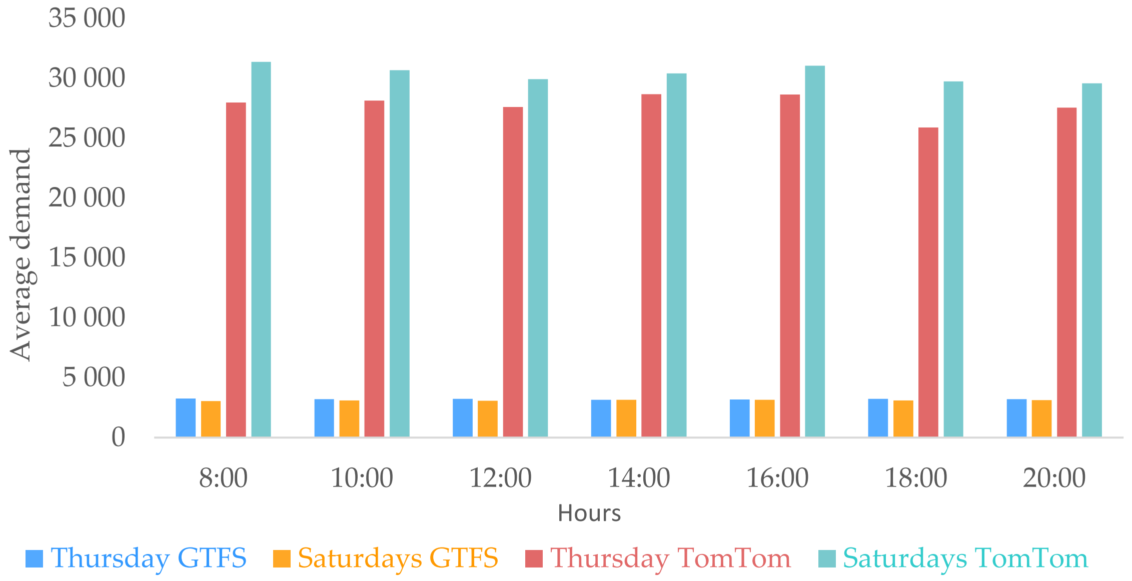


Figure 3. Average population covered according to hours.

3.2. Population Allocated to Shopping Centers Using the Maximize Market Share Solution

The Maximize Market Share solution was employed to evaluate the impact of changes in public transportation frequencies and private transportation congestion on the demand share assigned to shopping centers in the presence of competitors.

The proposed solution maximizes the market share of a given set of facilities. The total market share is the sum of all customer weights for valid demand points. The market share solution is a gravity model that allocates demand to each location using information about the importance (weight) of the company's facilities and the weight of competitors' facilities (Environmental Systems Research Institute). According to this solution, the population of a census tract is not assigned to a single center; instead, the population of the tracts is distributed among nearby centers based on distance and size.

The market share solution was developed using existing shopping centers (mandatory candidates) and the centroids of census tracts in Madrid (demand). The location-allocation model was implemented using public transportation (GTFS) and private transportation (TomTom) networks.

Once again, dynamic scenarios were developed by selecting two days of the week (Thursdays and Saturdays) and various time slots (8:00 h, 10:00 h, 12:00 h, 14:00 h, 16:00 h, 18:00 h, 20:00 h). The impedance parameter for a 10 min travel time was established. The attraction weighting for shopping centers was the Gross Leasable Area (GLA), which is a standard indicator of shopping center size, while the population of each census tract determined the population demand weight. Table summarizes the model results obtained using the GTFS network. The meaning of each column in the table is explained for clarity. The first column displays the hours used to run the location-allocation models. The second and sixth columns contain the population assigned on Thursdays and Saturdays. The third and seventh columns show the percentage of the assigned population relative to the total population obtained from the 2020 census (5 779 974 inhabitants). Finally, the fourth, fifth, eighth, and ninth columns indicate the absolute and percentage increases compared with the reference hour (18 h).

The assigned population was higher on Thursdays than on Saturdays. Hours 16:00 h and 20:00 h were observed to register lower values than the reference hour, whereas the remaining hours recorded higher demand. Focusing on Saturdays, the percentage increase for all hours was negative, except for 14 h.

Table 4. Population allocated to shopping centers at different times of the day using the GTFS network.

Hours	Thursday 10 min				Saturdays 10 min			
	Total	%	Inc.	Inc%	Total	%	Inc.	Inc%
8:00	1 129 561	19.5	87 119	8.4	972 942	16.8	-35 650	-3.5
10:00	1 087 069	18.8	44 627	4.3	958 090	16.6	-50 502	-5.0
12:00	1 071 123	18.5	28 681	2.8	937 018	16.2	-71 574	-7.1
14:00	1 050 334	18.2	7 892	0.8	1 033 056	17.9	24 464	2.4
16:00	1 029 206	17.8	-13 236	-1.3	981 320	17.0	-27 272	-2.7
18:00*	**1 042 442**	**18.0**	**0.000**	**0.0**	**1 008 592**	**17.4**	**0.000**	**0.0**
20:00	1 007 033	17.4	-35 409	-3.4	996 535	17.2	-12 057	-1.2

However, using the TomTom network yielded different results. First, a demand above 92 % was assigned on both days; furthermore, on Thursdays, there was an increase in all hours compared to the reference hour (18 h) whereas, on Saturdays, there were few changes between the different hours studied (Table). These few changes can be partly explained by the fact that weekend activities in the city slow down, resulting in smooth traffic flow during the day.

Table 5. Population allocated to shopping centers at different times of the day using the TomTom network.

Hours	Thursday 10 min				Saturdays 10 min			
	Total	%	Inc.	Inc%	Total	%	Inc.	Inc%
8:00	5 453 046	94.3	1 171 55	2.2	5 548 412	96.0	27 820	0.5
10:00	5 466 652	94.6	130 761	2.5	5 538 004	95.8	17 412	0.3
12:00	5 422 638	93.8	86 747	1.6	5 529 474	95.7	8 882	0.2
14:00	5 484 225	94.9	148 334	2.8	5 537 742	95.8	17 150	0.3
16:00	5 485 009	94.9	149 118	2.8	5 545 828	95.9	25 236	0.5
18:00	**5 335 891**	**92.3**	**0.000**	**0.0**	**5 520 592**	**95.5**	**0.000**	**0.0**
20:00	5 433 244	94.0	97 353	1.8	5 508 003	95.3	-12 589	-0.2

Table summarizes the differences between the days and networks analyzed. Public transportation is less efficient on Saturdays than on Thursdays, as evidenced by the negative percentages at various hours.

On average, weekends leave about 7 % fewer people unassigned compared with Thursdays, with the most significant impact being at 8 o'clock, with a decrease of around 14 %. The opposite occurs with the private transportation network, which provides excellent coverage on Saturdays. On average, with the private transportation network, approximately 92,478 more inhabitants (2 %) are served on Saturdays than on Thursdays. The most significant impact was recorded at 18 h, which coincides with the time when Madrid residents typically visit shopping centers on weekends.

Table 6. Differences between the allocated population (Saturday-Thursday).

Hours	GTFS		TomTom	
	Total	%	Total	%
8:00	-156 619	-13.9	95 366	1.7
10:00	-128 979	-11.9	71 352	1.3
12:00	-134 105	-12.5	106 836	2.0
14:00	-17 278	-1.6	53 517	1.0
16:00	-47 886	-4.7	60 819	1.1
18:00	-33 850	-3.2	184 701	3.5
20:00	-10 498	-1.0	74 759	1.4

Figure 4 shows the model results when using the GTFS and TomTom networks. The brown stars represent the locations of actual shopping centers; the brown squares indicate shopping centers with no assigned demand. The gray points refer to unassigned locations. In contrast, brown lines indicate shopping centers where demand is moving.

On both days (Thursdays and Saturdays), many census tracts (gray points) were unassigned to shopping centers, especially in the central part of the study area. In addition, shopping centers should obtain assigned demand locations (brown squares) (Figure 4-12). Furthermore, using the TomTom network (private transportation) provides better coverage than that obtained using public transportation. However, certain uncovered areas (gray points) were observed, especially at 18 h on Thursdays (Figure 13-14), as it became difficult to reach a shopping center within 10 min. This behavior may be related to the fact that 18 h is a time of congestion in Madrid. When comparing Thursdays and Saturdays, it is observed that the number of uncovered sites decreased on Saturdays at all hours due to a more significant population assignment.

When comparing Thursdays and Saturdays, it is observed that unassigned sections decrease during the weekend in all time slots due to a more significant population assignment on weekends (Figures 13-14).

Comparing the results obtained with the solutions of maximizing market share and maximizing attendance, it is found that the dynamism of GTFS and TomTom networks has a significant impact. Figure 8 summarizes the assignment percentages obtained using both solutions. The vertical axis represents the proportion of the assigned populations. The horizontal axis shows the number of hours used in model development. At the same time, the colors of the bars represent the days and networks used.

It is observed that with the solution of maximizing market share, much more demand is assigned than with the solution of maximizing attendance. For example, with the GTFS network, an average of 12 % more population was assigned for both days. Compared to the TomTom network, this rose to nearly 50 %. It is also observed that with the attendance maximization solution, values exceeding 40 % of the assigned population are reached in all time slots with the TomTom network. Meanwhile, with the shared market maximization solution, this figure exceeds 90 %.

The differences between the results obtained using the two solutions have several possible explanations. First, the objective functions of the maximizing attendance algorithm and the market share maximization solution are entirely different. In particular, the attendance maximization solution assigns the most significant population at a given time. The assigned population decreased as the distance between facilities and user locations increased. In addition, the solution assigns a demand to a single shopping center (the closest one).

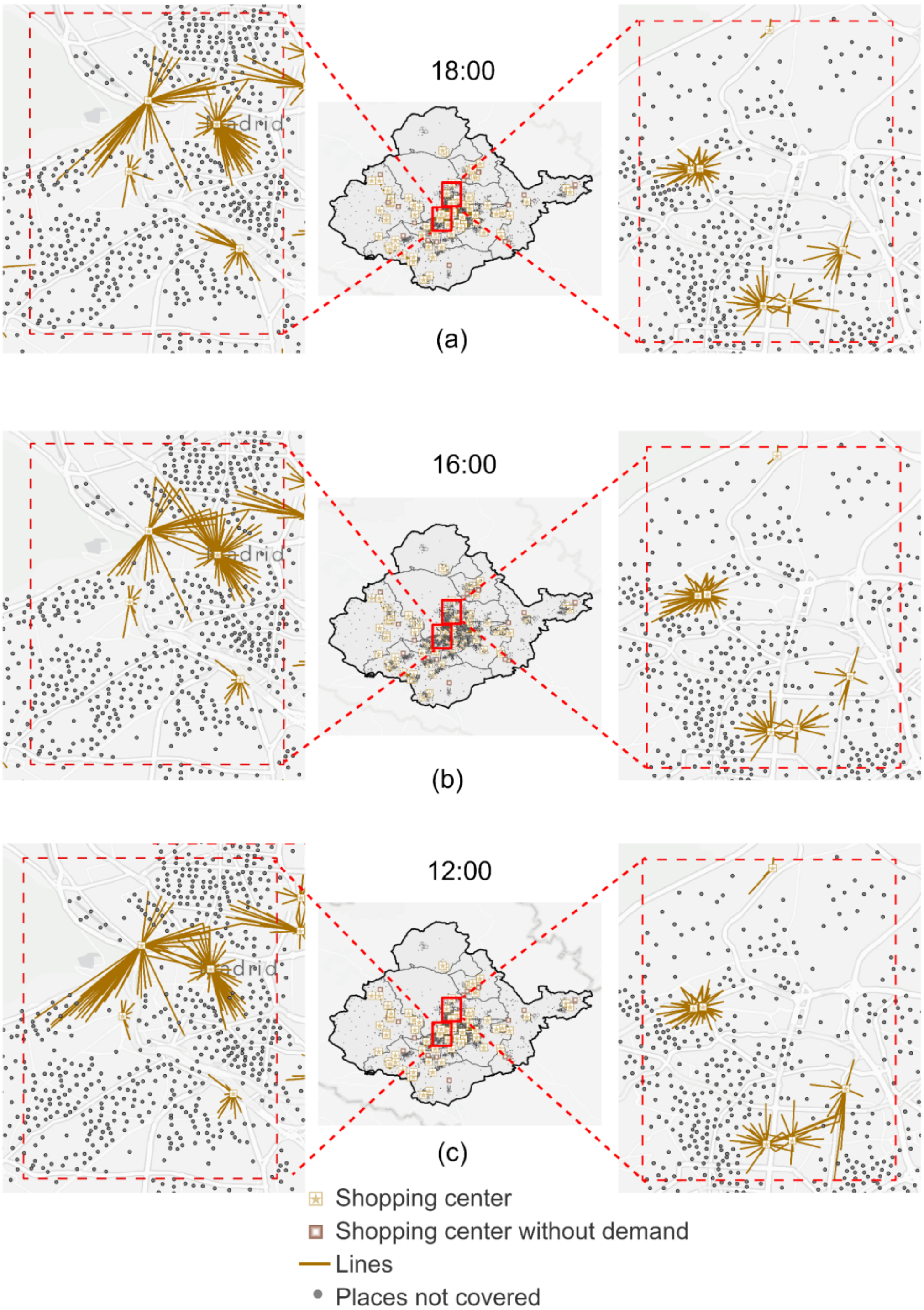


Figure 4. Details of unallocated census tracts for Thursdays using the GTFS network. (a) at 18:00 h; (b) at 16:00 h; (c) at 12:00 h.

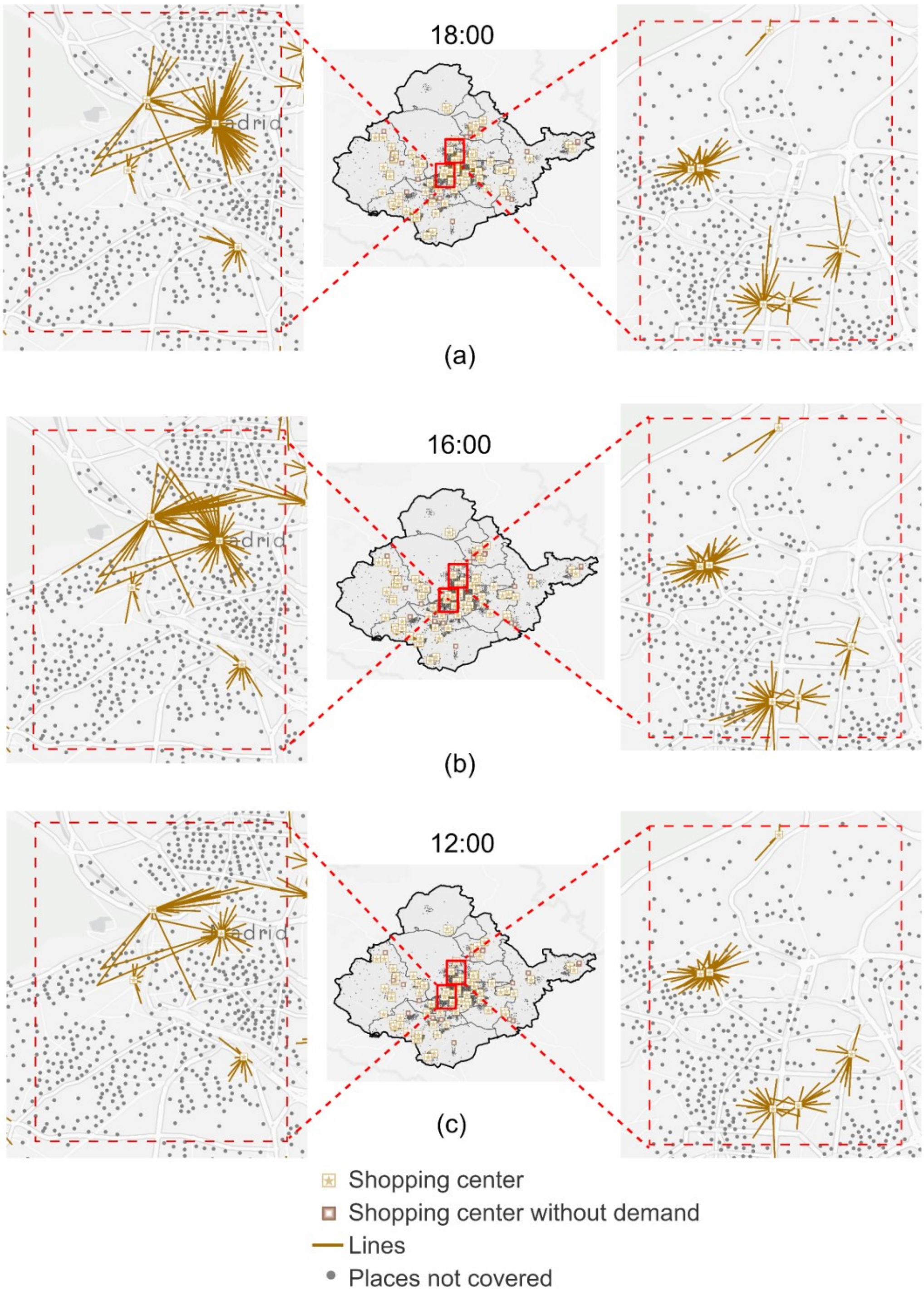


Figure 5. Details of unallocated census tracts for Saturdays using the GTFS network. (a) at 18:00 h; (b) at 16:00 h; (c) at 12:00 h.

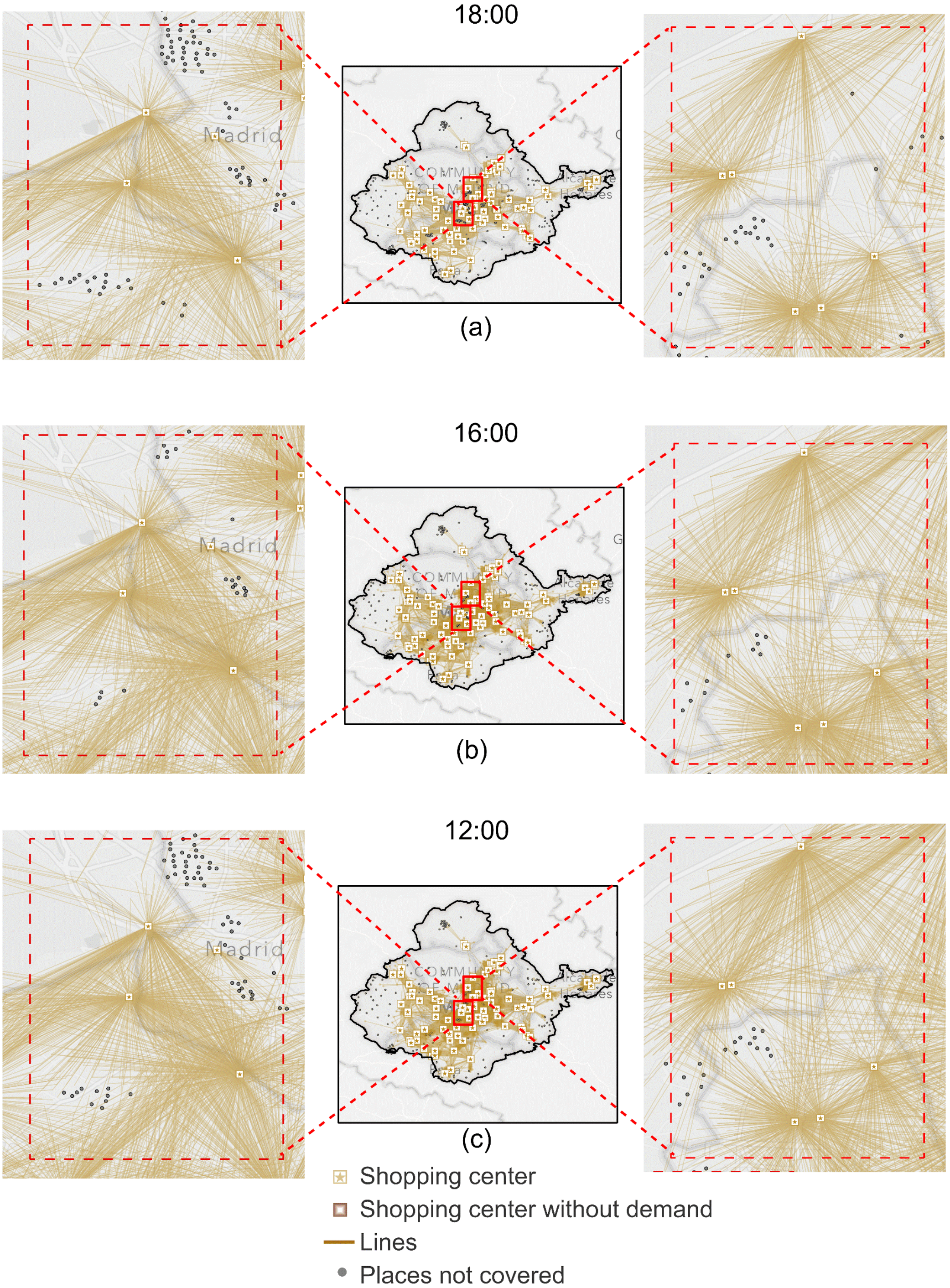


Figure 6. Details of unallocated census tracts for Thursdays using TomTom network. (a) at 18:00 h; (b) at 16:00 h; (c) at 12:00 h.

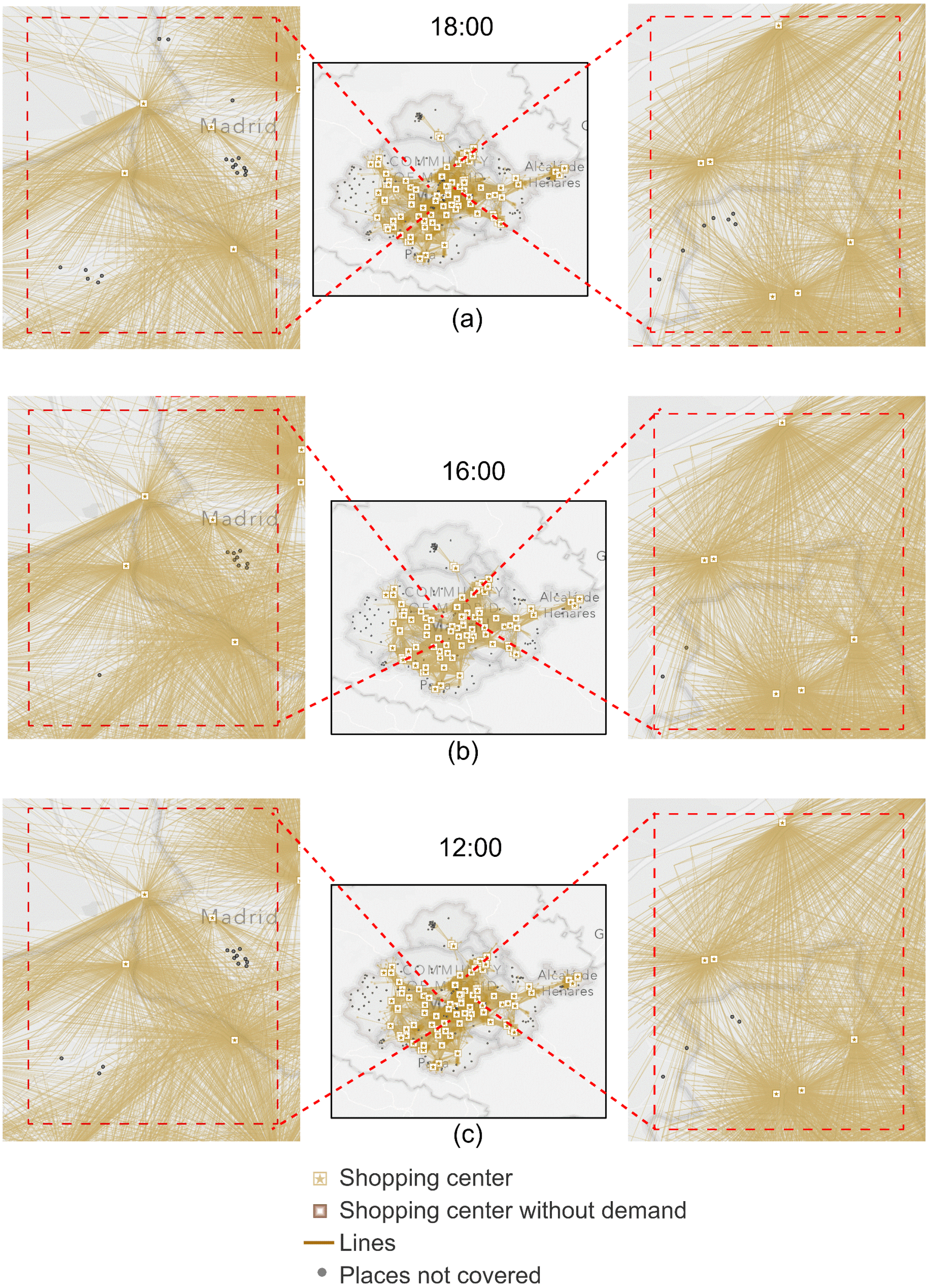


Figure 7. Details of unallocated census tracts for Saturdays using TomTom network. (a) at 18:00 h; (b) at 16:00 h; (c) at 12:00 h.

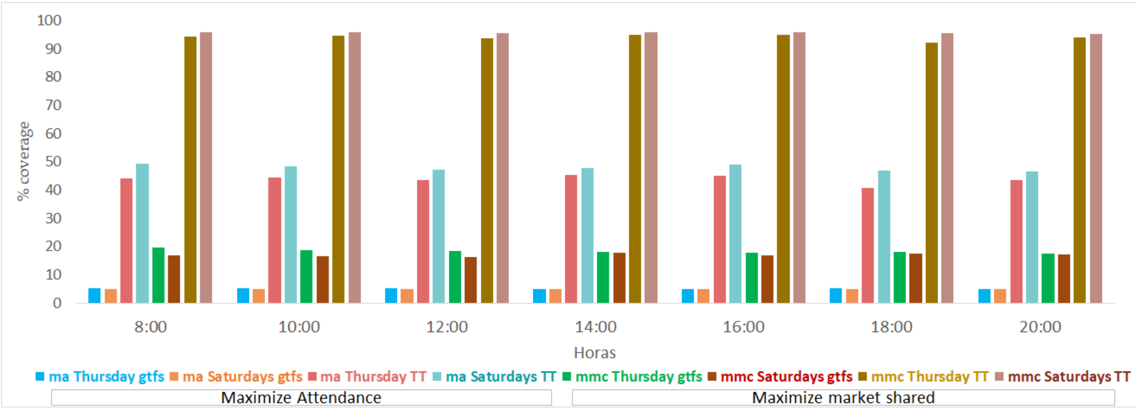


Figure 8. Percentage of the allocated population according to the solution used (GTFS network and TomTom).

In contrast, the shared market maximization solution uses another variable that influences model results. To develop the proposed solution, all possible information about competitors is required. For example, in this study, the gross leasable area of each shopping center was used (a variable commonly used in models with competitors) to attract demand points. Furthermore, a demand point within the established time threshold is assigned, in its entirety, to one or more shopping centers. At the same time, the population is assigned proportionally to the attractiveness of each shopping center.

Second, the impact of public and private transportation networks is also notable. The public transportation network may influence the results, mainly because of the different travel frequencies during the day. The attendance maximization solution algorithm affects the percentage of assigned populations because only a portion of the demand is distributed to a shopping center. In contrast, a shared market maximization solution distributes the population among several establishments. On the other hand, with a private transportation network, one has more freedom to visit shopping centers. The attendance maximization solution was more affected by vehicle congestion because the demand was allocated to the nearest shopping center. In contrast, a shared market maximization solution can be allocated to one or more centers.

4. Discussion

This study aimed to evaluate how dynamic transport conditions, specifically public transit frequency and road congestion, affect the demand coverage of shopping centers in the Madrid metropolitan area. We created two location-allocation models. One model focuses on maximizing attendance. The other aims to maximize the shared market. Both use dynamic networks from GTFS and TomTom Big Data sources. These models allowed us to simulate real-world variations in accessibility based on time of day and mode of transport.

The results reveal that demand captured by shopping centers is susceptible to changes in network conditions. For instance, in the GTFS-based model, coverage was significantly higher on weekdays than on weekends due to more frequent service schedules. The TomTom-based model had better coverage on weekends. Lower congestion made it easier for vehicles to access the area. In both cases, network dynamics resulted in significant differences in spatial coverage. This shows that static models might not accurately reflect service reach and market competition.

These findings connect with new research on accessibility that considers time changes (e.g., Braga *et al.*, 2023; Moya-Gómez & García-Palomares, 2017). They also expand the study to the less explored area of shopping mall location planning. Our approach differs from earlier studies that focused on average travel times or static networks (Ahmad *et al.*, 2017; Ahmadi & Ghezavati, 2020). We focus on how accessibility varies over time and among different users.

From a practical standpoint, the use of dynamic transport networks enables commercial planners to adjust operations in response to temporal demand shifts. Staff allocation, business hours, or promotional campaigns could be optimized based on hourly accessibility patterns. Additionally, this method can be applied to other urban services, such as pharmacies and restaurants. It can work in cities that have similar data systems.

Despite its contributions, the study has limitations. The models assume homogeneity in consumer behavior and do not yet integrate socio-demographic or behavioral attributes. Data limitations, especially with proprietary Big Data sources like TomTom, create challenges. These challenges include access issues, interoperability problems, and processing needs. Moreover, the models do not currently account for external factors such as pricing strategies, land-use regulations, or commercial leasing dynamics.

Future research could explore the integration of consumer data (e.g., transaction records, foot traffic counts) to enhance demand modeling. Incorporating real-time data streams or comparing performance across different traffic datasets (e.g., HERE, Waze) could also provide new insights. Additionally, examining the relationship between flexible business hours and changing accessibility patterns is a new area of research that has significant policy implications.

In conclusion, this study demonstrates that incorporating time factors into location-allocation models enhances their realism. It also enhances their usefulness in making decisions for commercial planning. Utilizing GTFS and TomTom data enables us to comprehend the intricate nature of urban systems. This approach also builds a solid base for future research on dynamic service accessibility.

Acknowledgments

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