Mobility patterns of satellite travellers based on mobile phone cellular data

Gábor MICHALKÓ[1], Márton PROROK[2], Attila Csaba KONDOR[2], Noémi ILYÉS[3] and Tünde SZABÓ[4]

Abstract

For a long time, tourism statistics were the only reliable source of information on tourism mobility. Tourism statistics are inadequate for the analysis of tourist mobility within state borders and across Schengen Borders without using registered accommodations. Big data offers the opportunity to gain a better understanding of tourism movements, for example, same-day tourist flows in metropolitan areas. Here, we introduce the concept of the satellite traveller to more effectively investigate the nature of tourism between the large city and its surroundings. As tourists communicate via cellular devices, the use of mobile phones offers an opportunity for researchers to explore the mobility pattern of tourists. In this article, we discuss the specificities of mobility in Hungary by SIM card users registered in foreign countries. The analysis is based on the Telekom database. We seek to answer the question to what extent the information from the satellite tourists' mobile phone use can help to understand their movements and to identify frequented places less commonly accounted for in tourism statistics. The most important findings of our investigation are (1) the confirmation of former knowledge about spatial characteristics of same-day tourist flows in the Budapest Metropolitan Region, (2) the insight that far away settlements are also visited by satellite travellers, and (3) the methodological limitations of mobile phone cellular data for tourism mobility analysis.

Keywords: big data, metropolitan region, same-day visit, unconventional tourism, Budapest

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Introduction

The city-region has been a focal point in the history of travel, from the time of Thomas Cook to present day, but particularly during the dynamic development of the tourism industry from the 1960s onward (Hua, H. and Wondirad, A. 2021). Settlements located in an agglomeration are integral supporters of tourism of the nearby metropolis like satellites orbiting in the Earth's gravitational field, ensuring the efficient communication of people. These so-called satellite settlements provide additional labour force and purchasing power for the successful operation of the metropolis, moreover, they also induce flows, especially because of their role in the tertiary or quaternary sectors (Burke, J. 1986; Merrilees, B. *et al.* 2013). The essence of the phenomenon described in this study as *satellite tourism* is the tourist mobility between the large city and its surroundings, without overnight stays (i.e. day trips; Stetic, S. *et al.* 2011). The nature of satellite tourism may be similar in many respects to the tourist behaviour observed in transit settlements, namely in terms of length of stay and expenditure (Kincses, Á. *et al.* 2017). The

[1] Geographical Institute, Research Centre for Astronomy and Earth Sciences (MTA Centre of Excellence), Budaörsi út 45. H-1112 Budapest, Hungary; University of Pannonia, Egyetem utca 10. H-8200 Veszprém, Hungary. E-mail: michalko.gabor@csfk.org

[2] Geographical Institute, Research Centre for Astronomy and Earth Sciences, Budaörsi út 45. H-1112 Budapest, Hungary. E-mails: prorok.marton@csfk.org, kondor.attila@csfk.org

[3] Corvinus University of Budapest, Fővám tér 8. H-1093 Budapest, Hungary. E-mail: noemi.ilyes@stud.uni-corvinus.hu

[4] GEOInsight Ltd., Budapest, Brassó út 5. H-1112 Budapest, Hungary. E-mail: szabo.tunde@geoinsight.hu

main difference is the ease of returning to the nearby city, which, unlike transit tourists, does not put satellite travellers under time pressure, allowing them to spend their free time more comfortably, get to know the place better and enjoy more colourful experiences.

The need for a better understanding and more accurate observation of satellite tourism induces the development of the available methodological arsenal. The understanding of certain phenomena and processes of metropolitan tourism has been a focus of research studies for a long time (Girardin, F. *et al.* 2008; Yang, Y. 2012; Kádár, B. and Gede, M. 2013), but the geographical extent of the same-day tourist mobility between the metropolis and its agglomeration zone has been neglected. This topic fits well with invisible tourism under the theoretical umbrella of unconventional tourism mobility (Kádár, B. and Gede, M. 2022; Kovalcsik, T. *et al.* 2022; Timothy, D. *et al.* 2022; Tóth, G. and Kincses, Á. 2022) and enriches the knowledge about destinations involved in same-day visits (Wynen, J. 2013a, b) and their archetypical consumers, the day trippers (Murillo, J. *et al.* 2013).

In our study, we seek to answer the question of the geographical range of foreigners' journeys to and from Budapest, the capital of Hungary, that are taken within a 24-hour period. Budapest is a popular destination for international tourists (especially among young visitors) because of its favourable geographical location, wide range of tourist attractions (e.g., baths, ruin bars, UNESCO World Heritage Sites) and relatively affordable prices for goods and services (Irimiás, A. 2010; Pinke-Sziva, I. *et al.* 2019). In addition to Prague (16.4 M) and Vienna (15.3 M), Budapest (9.4 M) also recorded significant amounts of international tourist nights in 2019, with the Austrian capital having the strongest link in terms of tourist flows (Kádár, B. and Gede, M. 2021). Like other European capitals (Freytag, T. 2010), the surroundings of Budapest are very popular with international day trippers, mainly Szentendre (pedestrian street milieu), Gödöllő (royal palace), and Visegrád (panorama on the Danube river bend).

This study offers an opportunity to improve the methodology for tourism-oriented cognition based on the cellular information of mobile phones. Given the negative impact of the COVID-19 pandemic on tourism, the research was based on data from 2019, the last undisrupted year for passenger traffic. A substantive part of the study was based on the analysis of a huge database of geo-coordinates from mobile phone calls placed within the municipality in 2019, using simple and complex mathematical, statistical and geoinformatics methodologies. The database contains information on the calls (data traffic) of foreigners who made the first and last calls from Budapest on the selected days between 0–24 hours and who also made at least one other call (data traffic) in Hungary. We seek to answer the question to what extent the information from the satellite travellers' mobile phone use can help to understand their movements and to identify frequented places less commonly reflected in tourism statistics. The results contribute to broadening the theory of unconventional tourism mobility to a deeper understanding of the nature of satellite tourism and to the development of a tourism-oriented research methodology based on mobile cellular data.

Big data in tourism mobility research

The increasing use of info-communication technologies (ICT) and big data, including mobile phone network data for modelling location and urban mobility networks, has opened new perspectives in modelling human mobility (Wang, Z. *et al.* 2018; Huang, B. and Wang, J. 2020). Individuals leave digital footprints in geographical space. The human digital footprint is a widely studied area that increasingly uses data integration methods to generate information on individuals' spatial presence and movement. Data sources can either be terrestrial or applied to various remote sensing technologies (Sagl, G. *et al.* 2014; Sagl, G. and Resch, B. 2015). Terrestrial data sources are usually called geospatial big data. They are comprised of information on daily human activities. Data are collected either by data service providers in the form of mobile cell and cellular signalling data and GPS positioning data (Steenbruggen, J. *et al*. 2013; Vanhoof, M. *et al*. 2018; Zhang, Y. *et al.* 2019; Mata, F.J. *et al*. 2020) or by business services as a by-product provided in the form of POS-terminal data or housing transactions data, or they can be crowed-sourced by social media check-ins and fitness applications, etc. (Thakuriah, P. *et al.* 2020). The spatial and temporal resolution of geospatial big datasets has grown over time. Telecommunication network data, called Call Detail Records (CDR), are widely involved in social and geographical analyses, specifically in urban studies (Louail, T. *et al*. 2014; Pucci, P. 2015; Jiang, S. *et al*. 2016; Razavi, S.M. *et al*. 2018; Egedy, T. and Ságvári, B. 2021).

Human mobility patterns show specific regularities: individually varying travel distances and a defined probability of returning to frequented locations are the most striking characteristics (González, M.C. *et al.* 2008). A periodic recurrence in mobility patterns implies that individual spatiotemporal distribution is heavy-tailed. That means most people spend most of their time in a handful of locations. Meanwhile, a smaller set of individuals spends their time in a large variety of locations, that contribute less than 1 percent to an individual's time consumption (Bayir, M.A. *et al*. 2009). Candia, J. *et al*. (2008) highlighted that spatiotemporal dynamics follow daily and weekly commuting patterns in agglomeration areas. The periodicity observed in the CDR data enables us to focus on higher spatiotemporal granularity.

The penetration of the social physics approach and its analytical framework has been accelerated by the growing number and depth of the available datasets. Statistical data and surveys are appropriate measures for recognizing the inherent structure of tourism-related mobility networks and exploring the behavioural patterns and motivations of the actors involved. High-scale human mobility databases, however, provide significantly more information in terms of representation and behavioural pattern discovery compared to classical statistical data collection and processing methods.

Graph-analytical tools, on the other hand, prove to be insufficient for the inclusion of the geographical dimension as an explanatory factor in tourism research (Hannam, K. *et al.* 2014). Research about interconnectedness in tourism, such as destination relationships, can be conducted by analysing the internal and external links of spaceless nodes. In this case, the online connectivity (e.g., browser searches) and offline connectivity (e.g., sequences of places which were visited on a trip) of the network nodes that constitute a local system can be compared with other local tourism networks. The network topology of tourism nodes can be approached in a similar way in global comparisons (Baggio, R. 2020). Unlike spaceless network investigations, those that apply spatial dimensions in a systematic way and as an explanatory factor are often conducted for policymakers (Chu, C.P. and Chou, Y.H. 2021), often in the fields of tourism transport infrastructure planning (Qian, C. *et al.* 2021) or heritage tourism (Liu, Z. *et al.* 2022). A detailed overview of the databases used for tourism research and visitor tracking has been given by Reif, J. and Schmücker, D. (2020). In destination management, not only the patterns and dynamics of visitation but also the order of places visited and the time spent at a given location can provide valuable information (Ahas, R. *et al.* 2008, 2010; Raun, J. *et al.* 2016; Saluveer, E. *et al.* 2020; Luštický, M. and Štumpf, P. 2021).

Mobile cellular data for better understanding of daily tourist flow

There are critiques on the efficacy of geospatial big data (including mobile cellular data), which have been relevant in our work as well. Among these, the positioning accuracy resulting from the tower coverage currently is an inescapable limitation, which significantly hinders the resolution of human mobility mapping. Another limiting factor is the event-dependent nature of the sampling. Data is only generated when an event has occurred on the network. Smartphones tend to log in at least once every 30 minutes but devices using less complex technology do not communicate with towers outside of events (Reif, J. and Schmücker, D. 2020). Daily visitor traffic and commuting traffic can be similarly defined by specifying a sleeping point and daytime stopping point. The sleeping point can be identified by the location of the first and last events that occurred during the day and can be interpreted as the individual's location at home. Our analysis targets daily visitor traffic. Therefore, we are looking for individuals who are spending their days away from their sleeping point but return for nights. That implies that in cases where the first and last event differs, even due to the inactivity of the device, the user is not included in the searched manifold, and the user's mobility data is not incorporated into our dataset. The phenomena of data loss are a commonly cited shortfall of big data processing. However, there are techniques to reduce the amount of data lost. The more precisely we are able to define the target population, the less data loss we experience.

In this study, our target population was satellite travellers using the Hungarian MTelekom network with a foreign SIM card. Our interpretation was that they started their first and initiated their last event of the day from Budapest but also gave a signal from a location outside Budapest during the day. The target group of tourism-purpose visitors can be easily separated from the professional traffic of non-Hungarian residents based on the functional distribution of places. Commuting out of the city is a non-typical movement, even among Hungarian SIM card holders, as the spatial distribution of workplaces in the Budapest Metropolitan Region is concentrated first and foremost in the central city and less significantly in the extended industrial areas located in the functional metropolitan area and the urban periphery (Dövényi, Z. and Kovács, Z. 2006; Szabó, T. *et al.* 2014). Workplaces are concentrated in specific delineated metropolitan areas, corresponding to industrial areas (Egedy, T. *et al.* 2017). The Budapest Metropolitan Region shows an extremely concentrated distribution regarding institutional amenities (only one university is located there) and recreation and sports facilities, which implies that daily commuting outside of the city for study and other purposes is also infrequent among Hungarian citizens. We concluded that the spatial distribution of workplaces in the Budapest Metropolitan Region differs significantly from the topography of places of tourist destinations. Therefore, we can safely isolate the tourism traffic of non-Hungarian mobile phone users from professional traffic.

In our case study, we sought to understand the processes, driving forces and dynamic changes in space when it comes to non-Hungarian satellite tourism traffic in order to be able to correctly interpret a large amount of data and the phenomena it reveals. For this reason, we decided to adopt a classical social geography approach without using the network science tools applied in mainstream science. Network science tools are mainly used to analyse the interconnectedness of spatial relationships, which have little added value in studying a local system and interpreting its operational regularities.

Clustering as a methodological tool for generalising human movements

We consider quantitative tools such as spatial-temporal clustering valuable data reduction and generalisation methods. We adopt the interpretation of Yuan, Y. and Raubal, M. (2012) when we use the inter-municipal clustering method, which provides a generalised description of individual movement processes: „Since individuals are atoms in an urban system, the spatio-temporal characteristics of an urban system can be viewed as a generalization of individual behaviour; therefore, mobile phone data also provide new insights into the analysis of the mobility patterns in urban systems." (Yuan, Y. and Raubal, M. 2012, 26.)

The first step in the clustering process is selecting an appropriate set of variables contributing to a mobility model explaining non-Hungarian visitors' movements. The clustering procedure involves grouping records – in our study, municipalities – in such a way that any subject within the resulting group is closer to all other elements in the group than to any other element outside the group. The concept of 'closeness' can be understood here in relation to the variables under investigation: for *n* observation units (that correspond to a specific settlement in the current case) if the number of variables under investigation is *m*, then the *n* observation units are placed in a standardised coordinate system of dimension *m* and then grouped through multiple iterations (Aldstadt, J. 2010). K-means clustering requires that the expected number of groups is determined in advance. In our case, we established six clusters in the first step and then reduced the number of clusters until we obtained a stable number of clusters based on the size of the cluster populations and the location of the cluster centres. The K-means clustering procedure selects random cluster centres according to the predefined number of centres and then calculates the distance of all elements from the initial cluster centres. Suppose a specific record is closer to another cluster centre than its centre according to the initial classification. In that case, the element is reclassified, the centres are recalculated, and the distance of the elements from the centres is measured. The iteration continues until all elements are assigned to the cluster centre closest to them. This multidimensional classification procedure contributes to typifying settlements according to the role they play in non-Hungarian visitors' satellite tourism traffic (Lingras, P. *et al.* 2011; Bose, I. and Chen, X. 2015; Wang, W. *et al.* 2018).

Data and experimental design

Data source

Our analysis was based on a mobile phone dataset provided by a Hungarian telecommunications operator. Data acquisition was accomplished by CSFK (Research Centre of Astronomy and Earth Sciences) with Hungarian Telekom Ltd (MTelekom), a member of the Deutsche Telekom Group. A research and development agreement was signed to explore the mobility performance of mobile phone users in Hungary in general and especially within the broader region of the Budapest Metropolitan Region. Hungarian Telekom is the long-term market leader in voice, multimedia and wireless services in mobile telecommunication, holding a stable market share of 45 percent in the Hungarian telecommunication market. According to the joint research agreement, Hungarian Telekom enabled CSFK to reach network system data via a SFTP-based interface. After a four-month-long period of data specification and data structuring and one extra month for the pilot run, data transmission started on 1 November 2017, and lasted until 30 November 2019. Data was uploaded daily. Via the data transmission interface, a package of four data files arrived at CSFK every day for two years. Files contained data referring to the daily event traffic, equipment in use, equipment attributes and actual network coverage.

Mobile phone network data analytics and visualisation reveal human mobility patterns reflecting individuals' real-world spatiotemporal dispersion. The geographical component of mobile telecommunication network data is registered, collected, and processed worldwide using similar technologies for data retrieval.

By establishing the research database, we retained the rich-in-detail feature provided by the exceptionally high amount and scale of data (e.g., geographical and temporal resolution, communication performance, etc.) and, at the same time, provided a comprehensive framework for deploying mobile cell data in applied social sciences. Our research database was built on individual equipment records. Each object corresponded to a mobile device equipped with a mobile SIM card, carrying out the multimedia transfer on the MTelekom wireless network. Each record, therefore, pertained to an individual user holding an MTelekom subscription or a non-Hungarian mobile device user using the MTelekom telecommunication network while staying in Hungary. The anonymity of the device holder was secured by hashing the equipment identifier by a randomly generated artificial ID. The equipment identifier was recoded every 24 hours. As a result, the investigation of mobility histories was only available for 24-hour timeframes.

Building the database

Six designated days have been selected from the two years of data available. We involved three public holidays (15 March 2019, 20 August 2019, 23 October 2019), and three other regular working days (Mondays) that followed the public holidays (18 March 2019, 26 August 2019, 28 October 2019). By selecting the dates involved in the analysis, we intended to exclude the domestic satellite traffic as much as possible to avoid interference with foreign satellite movements. On the occasion of long weekends and public holidays, a higher proportion of Budapest citizens (of both foreign and national origin) leave the city for a longer period, so they do not take part in satellite traffic. We summarised the events registered by non-Hungarian satellite travellers staying at and departing for any daily trip from Budapest. Satellite travellers were defined as device-holders registered abroad that started and ended their day in Budapest, meanwhile generating at least one event from a municipality other than Budapest between the first and last signal on the same day.

A typical problem that arises while processing mobile cellular data is that the system data collected from the towers is extremely noisy and subject to errors due to the incorrect registration of towers. Data noise, among others, results in extreme speeds (> 300 km/h) when it comes to mapping individual mobility trajectories. The error rate might reach 20 percent of all detected individual movements. Mobility trajectories are derived from registered telecommunication events, as they store the exact time of the event and the approximate location of tower, which carried out the event. A telecommunication event is defined as a user's communication with a telecommunication tower, regardless of whether voice, text or data is distributed during the event. In the scientific literature, CDR are the data detected on telecommunication towers, which approximate the content of what we define as an event. Event log data includes a timestamp, the duration of the communication, the technology used, the nature and direction of the communication, etc.

At the time of our study, 45,000 MTelekom towers served the national telecommunication network traffic. The geolocation of the coverage area's geometrical centre represents the towers' positions. The exact coordinates constitute a business secret. We assigned each tower to the basic administrative units of Hungary (municipal level), according to the distance of the tower position to the nearest residential area. In the current study, we did not apply the filtering of extreme speed event records since the procedure used standard speed to estimate the time spent by users. As a result of the procedure, extreme speed movement necessarily reduces the estimated time spent by users in each municipality to close to zero, so invalid records do not significantly change the satellite mobility model, and, at the same time, they do not cause data loss in the database.

It is essential to highlight that mobile cellular data processing does not allow for the accurate localisation of users. The granularity of localisation refers to the spatial resolution of the telecommunication coverage areas, ranging from a hundred meters to a few kilometres. In densely served areas, such as the peri-urban zone, the coverage areas of the towers overlap several times.

One of the consequences is the apparent hopping between municipalities: this occurs when a non-mobile user with a designated location close to the municipal boundary generates events on the towers assigned to one or the other municipality, depending on the utilisation of the towers. *Figure 1.* highlights the set of settlements located right next to the border of the municipality of Budapest, where a high number of foreign satellite travellers seemingly spent a

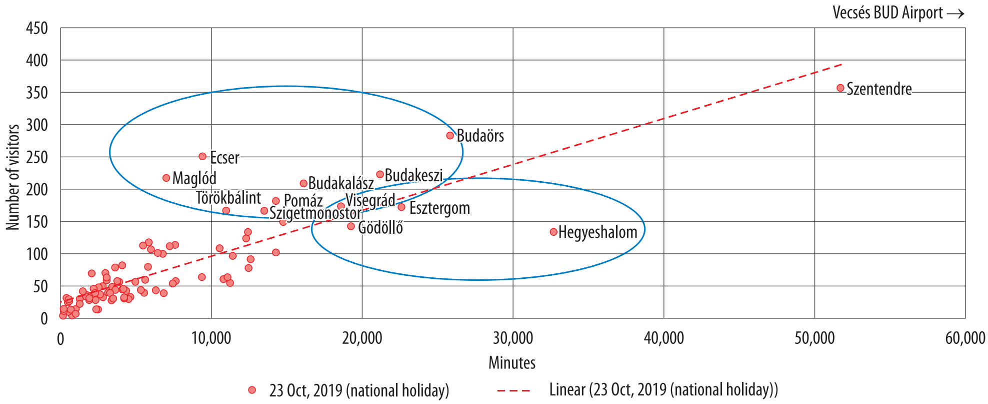

Fig. 1. Number of satellite travellers and time spent in each municipality on 23 October 2019 (national holiday). *Source*: Authors' own research.

limited amount of time. The reason behind this is the previously defined oscillation along the border region. In this case, our data show that the user may apparently cross the Budapest boundary several times without actually moving. This may result in incorrectly assigning a user to one or another municipality based on the events, and, as a result, falsely defining a user as a satellite traveller. We carefully considered removing the subset of adjacent locations from the analysis. As a result of the delayed and congested stages of urban development of the post-socialist era, some of the traditional cultural and economic centres of the urban periphery – such as Szentendre and Gödöllő – have been incorporated into the functional metropolitan area. Because of the functional diversity and architectural heritage, some adjacent centres may be satellite tourism destinations based on their merits (Fabula, Sz. *et al.* 2021). Therefore, removing the affected settlements from the analysis may imply a significant loss of data which would mask peculiar phenomena in an early research stage. We decided to keep the integrity of the initial dataset and carefully draw attention to the limitation of the methods applied.

As we can see in *Figure 1*, a strong positive linear correlation was observed, and municipalities fit the linear trend line. Vecsés, which accommodates Budapest Ferenc Liszt International Airport (IATA: BUD), was an outlier in terms of the number of visitors and time spent. The airport's outstanding satellite traffic is due to its peripheral location at the border between the city and the agglomeration. The same phenomenon occurred in the settlements at the city border: events were handled by towers located in both the agglomeration settlements and Budapest, making visitors' locations seem to oscillate on the city-urban periphery border.

All these uncertainties are pervasive for telecommunication big data sources, and indeed big data in general. Even so, the granularity, scope, frequency and representativity of the MTelekom dataset exceed most available data sources. This is because individual mobility histories are not even available for research purposes under the Hungarian corporate legal interpretation since the General Data Protection Regulation (2018) entered into force.

Spatial features of satellite tourism in the Budapest Metropolitan Region

Mobility formula for satellite tourism at the municipal level

We elaborated upon a mobility model of satellite tourism at the municipal level using minute-based location records and standard speed when calculating individual movement. Events were recorded at telecommunication towers in the form of CDR data. This dataset was complemented by the Customer Relationship Management (CRM) data generated by the service provider MTelekom, which captured users' demographics, subscription and device information. Only the country of subscription and device data were recorded for non-Hungarian users. If the service provider detected a non-Hungarian user participating in satellite tourism in the same municipality other than Budapest on two consecutive occasions, the time elapsed between the two events was attributed to that user ($T_{1,2}(i) = t_1(i)$), i.e. it was assumed that between the two events the user stayed at the municipality. If the user moved between two events, the airline distance between the geometric centroids (S_1, S_2) of the coverage areas was defined as the displacement vector (v_1). The user's individual mobility history was composed of a series of vectors ($v_{1,2}(i)t_1$, $v_{2,3}(i)t_2$, … $v_{n\text{-}1,n}(i)t_n$), summarised on a daily basis. In addition to the calculated values of the displacement vector, a record was made when the user continued to move from the previously registered settlement (L_1) to the municipality registered after that (L_2). In this case $T_1(i)L_1$, $T_2(i)L_2 \rightarrow v_{1,2}(i)t_1$, where $v_{1,2}$ corresponds to the displacement, and t_1 is the time elapsed between events (event-minutes).

The mobility model was designed to account for users who spend, from a tourism point of view, the relevant amount of time in the location. Therefore, we needed to filter out transit users in each location. To do this, we introduced a standard displacement speed set at 60 km/h due to airline movements. Knowing the speed and the displacement vector $v_{1,2}$, the time spent travelling (travel-minutes, $u_1(i)L_{1,2}$) could be estimated. Given a location L_1, the estimated time spent in the location (length of stay, t_1') is equal to the difference between the time spent between the events and the time spent travelling. The estimated time a user potentially spends in each settlement for tourism purposes, therefore, equals the time elapsed between the event logs in the two various places minus the time spent travelling:

$$t_n'(i)\ L_n = t_n(i)\ L_{n\text{-}1,n} - u_n(i)\ L_{n\text{-}1,n}$$

The lengths of stays calculated in this way were allocated to the municipalities concerned in equal proportions per user, i.e. half to $L_1(i)$, and a half to $L_2(i)$. We then summed up the estimated length of stay frequencies for each day, i.e. we determined how many users took up each length of stay value.

We aggregated the number of users and lengths of stays on the selected dates separately and then created three groups by simple weighted division into thirds. One-third of the users spent 1–12 minutes, another third spent 13–66 minutes and the remaining third spent more than 67 minutes (max. 1,281–1,440 minutes) in the municipality concerned. For these three groups of lengths of stays, we mapped the daily distribution of satellite travellers by the municipality. In the first group, transit visitors, who touched the municipality during their daily movements, were accounted for. The second group included satellite travellers who stopped in the municipality for a short period, for instance for resting, refuelling, shopping, etc. The third group included the satellite travellers we want to account for, who spend a longer period of time in a settlement before returning to Budapest.

Interpretation of the mobility formula by introducing cluster analysis

In order to understand the real-life implications of the generalised mobility model, we introduced three spatial variables: distance from motorways, distance from industrial parks and distance from Budapest *(Table 1)*. For each variable, the distance was given in linear distance calculated as the distance from the nearest motorway, the nearest industrial area and the distance from the Budapest geometric centre to the geometrical centre of the municipality concerned. The dis-

Table 1. Statistical parameters of the variables included in the explanatory model of K-means clustering (N = 3,154)

Per settlement		Range (= Maximum)	Sum	Mean	Std. deviation	Variance
Minutes spent, total, 15 March		*90,515*	*635,899*	*202*	*1,930*	*3,725,047*
of which	satellite transit (1–12 minutes)	3,026	12,929	4	56	3,094
	short stays (13–66 minutes)	22,288	77,315	25	406	165,169
	satellite tourists (67–1,281 minutes)	65,201	545,656	173	1,525	2,324,649
Pieces of equipment, total, 15 March		*1,547*	*7,245*	*2*	*29*	*824*
of which	satellite transit (1–12 minutes)	467	2,444	1	9	75
	short stays (13–66 minutes)	712	2,384	1	13	168
	satellite tourists (67–1,281 minutes)	368	2,417	1	8	58
Minutes spent, total, 18 March		*109,261*	*712,985*	*226*	*2,377*	*5,650,026*
of which	satellite transit (1–12 minutes)	2,920	14,145	4	56	3,116
	short stays (13–66 minutes)	25,136	96,222	31	474	224,805
	satellite tourists (67–1,281 minutes)	81,205	602,618	191	1,887	3,559,734
Pieces of equipment, total, 18 March		*1,758*	*8,342*	*3*	*34*	*1,133*
of which	satellite transit (1–12 minutes)	439	2,570	1	9	73
	short stays (13–66 minutes)	807	3,001	1	15	229
	satellite tourists (67–1,281 minutes)	512	2,771	1	10	108
Minutes spent, total, 20 August		*82,762*	*689,847*	*219*	*1,988*	*3,952,840*
of which	satellite transit (1–12 minutes)	2,260	15,499	5	46	2,129
	short stays (13–66 minutes)	19,781	85,032	27	377	141,772
	satellite tourists (67–1,281 minutes)	60,721	589,317	187	1,623	2,633,575
Pieces of equipment, total, 20 August		*1,302*	*8,671*	*3*	*27*	*716*
of which	satellite transit (1–12 minutes)	338	3,088	1	7	55
	short stays (13–66 minutes)	622	2,592	1	12	138
	satellite tourists (67–1,281 minutes)	342	2,991	1	9	79
Minutes spent, total, 26 August		*135,446*	*796,259*	*252*	*2,846*	*8,097,619*
of which	satellite transit (1–12 minutes)	2,951	16,665	5	59	3,434
	short stays (13–66 minutes)	31,689	110,427	35	590	348,172
	satellite tourists (67–1,281 minutes)	100,806	669,168	212	2,239	5,014,714
Pieces of equipment, total, 26 August		*2,024*	*9,762*	*3*	*39*	*1,517*
of which	satellite transit (1–12 minutes)	437	3,100	1	9	82
	short stays (13–66 minutes)	982	3,415	1	18	334
	satellite tourists (67–1,281 minutes)	605	3,247	1	12	151
Minutes spent, total, 23 October		*101,435*	*880,427*	*279*	*2,520*	*6,351,869*
of which	satellite transit (1–12 minutes)	3,052	19,844	6	64	4,068
	short stays (13–66 minutes)	23,189	105,878	34	446	198,645
	satellite tourists (67–1,281 minutes)	75,194	754,705	239	2,090	4,368,360
Pieces of equipment, total, 23 October		*1,674*	*10,679*	*3*	*34*	*1,176*
of which	satellite transit (1–12 minutes)	492	3,759	1	11	113
	short stays (13–66 minutes)	739	3,241	1	14	199
	satellite tourists (67–1,281 minutes)	443	3,679	1	11	124
Minutes spent, total, 28 October		*134,741*	*822,807*	*261*	*2,926*	*8,562,985*
of which	satellite transit (1–12 minutes)	3,156	16,298	5	65	4,219
	short stays (13–66 minutes)	29,507	111,871	35	560	313,206
	satellite tourists (67–1,281 minutes)	102,078	694,638	220	2,349	5,519,445
Pieces of equipment, total, 28 October		*2,017*	*9,634*	*3*	*40*	*1,570*
of which	satellite transit (1–12 minutes)	490	2,967	1	10	109
	short stays (13–66 minutes)	920	3,416	1	17	303
	satellite tourists (67–1,281 minutes)	607	3,251	1	13	162
Distance from motorways, km		*16*	*8,537*	*3*	*2*	*4,078*
Distance from Budapest, km		*288*	*457,334*	*145*	*58*	*3,377,982*
Distance from industrial areas, km		*34*	*31,116*	*10*	*6*	*33,911*

tance from motorways was introduced into the explanatory model as a type of urbanisation indicator. Our preliminary expectation was that the destinations preferred by foreign visitors are necessarily equipped with urban services, i.e. they are also attractive to international tourists in terms of the quality of service. The distance from Budapest was assumed to be an essential variable for satellite tourism. Still, precisely because of the development of the motorway network, there was a narrow range of potential destinations that were generally excluded from the daily visitor flow due to distance alone.

The distance from industrial parks was calculated using land use (OSM Landuse Landcover) data. 9,209 industrial land use sites were mapped in the whole country, with an average site area of 0.13 km^2. Our analysis included only medium and large industrial sites greater than 0.5 km^2 in size. A total of 200 industrial sites were selected across the country. The presence of industrial sites with a larger area was interpreted as an indicator of production activity in the municipality. Industrial production was assumed to be a tool for economic prosperity, especially in municipalities with less tourist attraction. Therefore, we expected an inverse correlation between the proximity of industrial parks and the number of visitors to municipalities involved in satellite tourism.

We examined the correlation between the spatial structural indicators introduced in the model, such as the distance from motorways, industrial areas and the Budapest city centre, and the satellite traveller flow indicators, i.e. the number of visitors spending longer periods and total time spent in the settlement *(Table 2).* Contrary to preliminary expectations, Budapest's proximity proved to have no impact on satellite tourism. Similarly, no correlation was detected between motorway access and satellite tourism. However, industrial areas showed a weak, significant negative correlation with non-Hungarian satellite travellers' mobility: the more attraction a municipality holds, the less the presence of industrial areas close to the municipality.

This correlation suggests that the integrity of tourist attractions within the residential urban fabric determines the appeal for foreign satellite travellers. It may also imply that settlements with a valuable heritage and appealing attractions have given less land area for industrialisation and logistics. If they have, these areas have been located at a suitable distance from tourism destinations of international interest. The result that the spatial dispersion of satellite traveller traffic does not overlap with the geographical distribution of industrial production also serves to justify our methodology. Theoretically, we could incorrectly identify a non-Hungarian employee living in Budapest and working in the agglomeration zone as a satellite traveller. However, industrial areas' proximity would positively correlate with visitor flow in this case. Thus, according to our definition, there is a high probability that the subset of non-Hungarian visitors filtered from the data excludes non-Hungarian commuting traffic for employment purposes.

Finally, K-means clustering was used to identify subsets of municipalities with similar characteristics based on the three correlated variables (distance from industrial areas, minutes spent, and the number of visitors – *Table 3*), but which differ significantly from the "behaviour" of other clusters. The result was a four-tiered typology of settlements grouped according to their role in satellite traffic. The vast majority of municipalities could be grouped into two clusters, which were uniformly unimportant in terms of visitor traffic but differed in economic nature from each other. In the third cluster, municipalities such as Vecsés (BUD) and Szentendre were the most important destinations for non-Hungarian satellite travellers. Finally, the fourth cluster included a reasonably narrow range of municipalities, mainly in the Danube bend and the agglomeration, with a few rural locations.

Watching the cluster-membership of municipalities *(Figure 2)*, four major trends can be identified when looking at the spatial distribution of non-Hungarian daily satellite visitors:

*Table 2. Co-movement of variables: correlation coefficient among the spatial-structural variables**

Per settlement		Distance from motorways	Distance from Budapest	Distance from industrial areas
		Pearson correlation		
Minutes spent, total, 15 March		*-.067*	*.014*	*-.092*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.045 -.037 -.073	.021 .018 .012	-.060 -.051 **-.101**
Pieces of equipment, total, 15 March		*-.050*	*.020*	*-.066*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.054 -.036 -.064	.023 .018 .017	-.067 -.051 -.086
Minutes spent, total, 18 March		*-.073*	*.016*	***-.102***
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.054 -.047 -.079	.027 .024 .014	-.072 -.067 **-.110**
Pieces of equipment, total, 18 March		*-.056*	*.024*	*-.076*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.064 -.046 -.063	.031 .023 .018	-.079 -.064 -.088
Minutes spent, total, 20 August		*-.085*	*.019*	*-.100*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.074 -.051 -.091	.027 .024 .016	-.088 -.064 **-.106**
Pieces of equipment, total, 20 August		*-.075*	*.026*	*-.087*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.091 -.050 -.083	.033 .024 .019	-.100 -.063 -.095
Minutes spent, total, 26 August		*-.071*	*.017*	*-.094*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.069 -.045 -.076	.027 .020 .015	-.085 -.061 **-.101**
Pieces of equipment, total, 26 August		*-.061*	*.022*	*-.079*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.081 -.045 -.066	.030 .021 .017	-.096 -.067 -.090
Minutes spent, total, 23 October		*-.088*	*.024*	***-.112***
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.075 -.057 -.092	.029 .022 .023	-.092 -.070 **-.117**
Pieces of equipment, total, 23 October		*-.076*	*.025*	*-.093*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.084 -.056 -.083	.031 .021 .021	-.100 -.069 **-.103**
Minutes spent, total, 28 October		*-.075*	*.019*	*-.100*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.066 -.051 -.079	.022 .025 .017	-.082 -.068 **-.106**
Pieces of equipment, total, 28 October		*-.063*	*.024*	*-.082*
of which	satellite transit (1–12 minutes) short stays (13–66 minutes) satellite tourists (67–1,281 minutes)	-.074 -.050 -.067	.025 .025 .020	-.089 -.067 -.090
Distance from motorways		*1.000*	*-.007*	***.228***
Distance from Budapest		*-.007*	*1.000*	*-.004*
Distance from industrial areas		*.228*	*-.004*	*1.000*

*Distance from motorways, from Budapest and industrial areas, and satellite tourism metrics, such as the number of visitors and tourism time spent on various days. Significance level (2-tailed) = 0.0000. Variable are significant at 5% level.

*Table 3. K-means clustering scoreboard, 23 October 2019, for visitors who spent more than 67 minutes in each municipality**

Indicators	Final cluster centres			
	Rural areas	Peri-urban areas	Points of interest of satellite tourism	Urban satellite destinations
	not affected by satellite tourism			
Distance from industrial areas, km	16.40	6.50	3.10	2.60
Time spent, minutes	31.84	128.36	62,100.25	12,811.87
Number of visitors	0.18	0.62	352.50	58.46

*The municipalities were clustered into four types: two rural types of municipalities not affected by visitor traffic (cluster 1: rural, not affected, and cluster 2: peri-urban areas, not affected), one highly visited, industrialised type (cluster 3: hot spots), and one urbanised type, attracting high-scale satellite traffic (cluster 4: urban satellite).

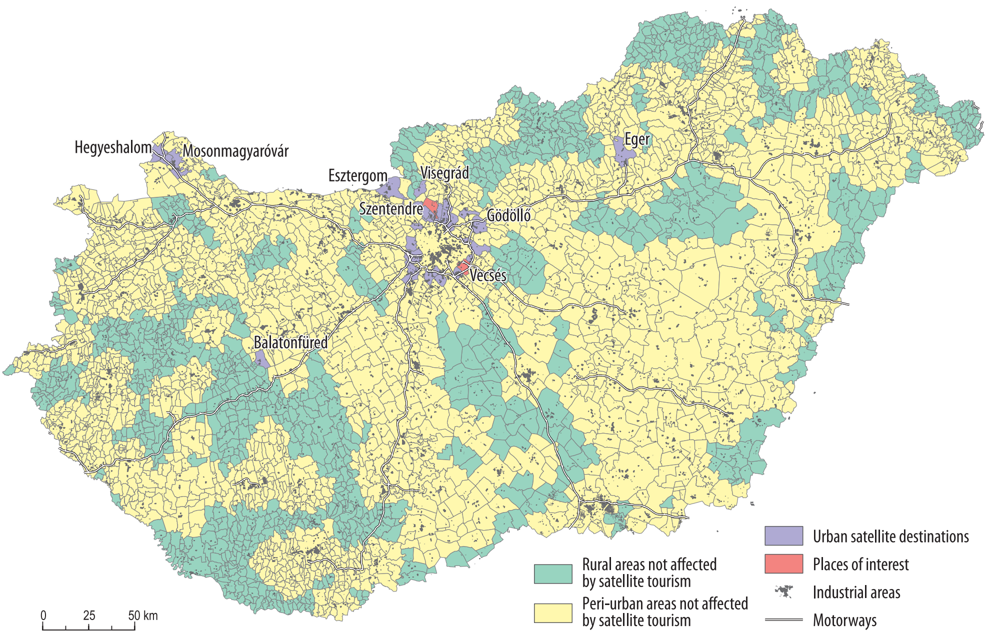

Fig. 2. Cluster membership of municipalities regarding to international visitors on 23 October 2019. *Source*: Authors' own research.

The most explicit and substantial traffic is heading towards the Danube Bend, with Szentendre, Visegrád and Esztergom being the main destinations. Many non-Hungarian visitors come here for longer stays.

The Budapest Metropolitan Region attracts high-scale visitor traffic, with Vecsés, as the airport's host municipality, standing out by far. The extreme visitor traffic flow evolves from peripheral locations, as the airport facility is supported by various towers both registered in Budapest and in the neighbouring municipalities around the airport. The visitors identified as taking part in satellite tourism in this locality do not actually return to Budapest; their movements are apparent because they are occasionally served by Budapest towers, but their location remains unchanged in the vast majority of cases. This phenomenon of 'apparent moving' results in the peaking traffic of the agglomeration municipalities. The over-representation of agglomeration municipalities is an outcome of technological limitation (network load-optimised service delivery).

Non-Hungarian visitors are heading towards the Western border of Hungary (Hegyeshalom, Mosonmagyaróvár) that incorporates the daily visitor flows to Austria and Slovakia, and reflects the daily city tours to Vienna and Bratislava. The large number of long stays at the border area is also apparent, since in fact the signals disappear at the border, but our method assumes a stop between the event traffic in the outbound and inbound directions. An indication of this is that we have assigned to border crossing a small number of visitors with very long stays. If data collection methods would enable tracking events beyond borders, the significance of the border-crossing settlements would immediately be reduced to a fraction, as visitors would appear elsewhere between two logins at the border area.

The tourist attractions Eger and Lake Balaton are also key contributors to visitor traffic, with Balatonfüred as main destinations for non-Hungarian satellite tourism flow, with some significant seasonal variations.

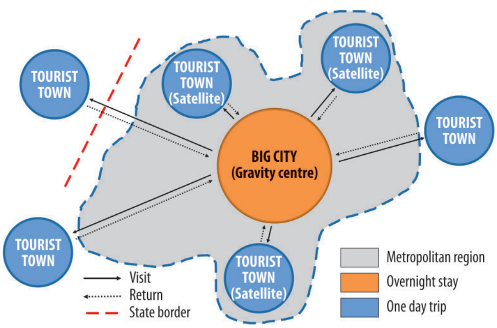

Fig. 3. Model of satellite tourism. *Source*: Authors' own design.

Discussion and conclusions

Satellite tourism is a phenomenon to be discussed under the umbrella of unconventional tourism mobility, which by nature is difficult to track because tourist consumption is not fulfilled, and the presence of tourists can be detected temporarily but is difficult to register (Belotti, S. 2019; Timothy, D. *et al.* 2022). The significant daytime tourist traffic in the agglomeration of large cities is rarely matched by the use of local accommodation services, so the tourism-based economy is one-sided, with moderate development in the accommodation sector and without the development of the night-time economy. Tourism receipts from leisure activities are mainly generated in agglomeration settlements, while the receipts from outward and return journeys to the big cities and overnight stays are mainly generated in central cities. The city's gravitational pull is due to its excellent international and domestic transport links, diversified accommodation, hospitality and retail offerings, and colourful leisure activities. After a while, or in the case of repeat visitors (Freytag, T. 2010), travellers of big cities become saturated with local experiences, and begin looking for a new impulse, which they can experience either in an individual or organized way in the agglomeration zone.

Based on our investigation of tourism mobility using mobile phone data, we have been able to define a model of satellite tourism *(Figure 3)*. The novelty of the model is that it interprets the notion of satellite tourism not only in terms of flows to the settlements traditionally surrounding a metropolis, but also integrates mobility outside the agglomeration and even beyond the national border for less than 24 hours. The model offers a new theoretical framework for understanding the tourist flows in towns involved in same-day visits because it describes a system of mobility between origin and destination settlements. As the studies on same-day visits have so far focused on destinations, mainly on the consumer behaviour of day trippers and its social, economic, and environmental impacts, the model can contribute to broadening the horizon of future investigations (Bauder, M. and Freytag, T. 2015; Bozonelos, D. 2020). Understanding the motivations behind tourists returning within 24 hours will help to better outline tourism development in the areas concerned (Surinach, J. *et al.* 2017). Mobile phone data can be very helpful in better understanding the mobility of satellite travellers, but the limitations of systematic observations using the same methodology mean that further procedural improvements are essential.

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