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Changing Mobility Lifestyle:
A Case Study on the Impact of COVID-19 Using Personal Google Locations Data

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ABSTRACT

The article is focused on a detailed micro-study describing changes in the behaviour of the authors in three months before and during the COVID-19 pandemic. The study is based on data from Google Location Service. Despite the fact it evaluates only three people and the study cannot be sufficiently representative, it is a unique example of possible data processing at such a level of accuracy. The most significant changes in the behaviour of authors before and during the COVID-19 quarantine are described and interpreted in detail. Another purpose of the article is to point out the possibilities of analytical processing of Google Location while being aware of personal data protection issues. The authors recognize that by visualizing the real motion data, one partially discloses their privacy, but one considers it very valuable to show how detailed data Google collects about the population and how such data can be used effectively.

KEYWORDS

Behavior Changes, COVID-19, Czechia, GIS, Google Locations, Mobility, Spatial Analyses

1. INTRODUCTION

After the sudden approach of COVID-19 pandemic to our lives, people have had to adjust daily routines according to nation-wide restrictions and anti-epidemic measures. Besides the general availability of data about COVID-19 disease, it is possible also explore and analyse personal data generated via mobile applications with a shared location. An important area of data analysis that is currently being worked on in connection to COVID-19 pandemic is the processing of data from mobile operators. In Czechia, such data are used in the so-called "smart quarantine" (a term used by regional hygiene administrations), which is based on the visualization of individual mobile phone data to for detect the movement of infected people. Based on the infected person's consent, the data is supplied to the specialists, who create so-called commemorative maps. Such maps serve as a graphical visualization of the individual's movement for the past five days. It then helps the infected individual to recall places of his movement and subsequently people he has met.

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The current position of the population can be detected based on a variety of large datasets (often called „big data“), whose importance is growing in recent years in all areas of human activity. Although the topic of big data has been intensively discussed in the last few years, the term originally appeared in connection with visualization more than 20 years ago (Cox & Ellsworth, 1997). Batty (2016) states that determining the boundary of what is and what is not big data is very relative because almost always in the last 60 years there were data sets that could not be processed by the then hardware and software. As a reason why the topic is widely exploited today, Batty mentions a significantly higher number of sensors and online data sources that can be processed. According to Batty, the key aspect of big data is the existence of mobile phones and the large amount of potential data associated with them. In a number of his publications (e.g. Batty, 2013; Batty, 2016), Batty mainly describes two main areas of big data that are used for urban studies, namely data from mobile operators and data from social networks. It is important to note that multinational private corporations such as Microsoft, Facebook, Google, Apple or even mobile operators, collect large amounts of data (which can be called big data due to its heterogeneity) on their users, which in the case of the COVID-19 pandemic appears to provide an opportunity to stop the uncontrolled spread of the disease.

In case of social networks, the analysis of big data is often performed on data from Twitter or Foursquare networks (Hawelka et al., 2014; Kocich, 2018), and such data is used to determine land-use (Frias-Martinez & Frias-Martinez, 2014; Roberts, 2017), defining the boundaries of spatial structures (e.g. Yin, Soliman, Yin, & Wang, 2017) or monitoring the mobility of people (Noulas, Scellato, Lambiotte, Pontil & Mascolo, 2012; Long, Jin, & Joshi, 2012; Noulas, Scellato, Mascolo & Pontil, 2011). Similarly, data from many other social networks are analyzed (Frothingham, 2014; Haworth, 2016; Selala & Musakwa, 2016), which also include networks focused on recording sports activities (e.g. Strava, Endomondo, Garmin, etc.). Based on the analysis of data showing the movement of sports activities, it is possible to identify the most frequently used cycle paths, problematic intersections, recreational areas, traffic behavior of mobility participants (Sun, 2017).

In the developed world, ownership of a mobile phone is taken for granted and therefore mobile operator data can serve as the best source for identifying the true location of the population over time. The problem with these data, however, is their unavailability, whether due to price, incompleteness, or other objective criteria. The issue of personal data protection also plays an important role, as data from mobile phones contain sensitive information. Nevertheless, the frequency of use of this data is increasing, especially because it brings valuable insights of real mobility patterns (Calabrese, Diao, Di Lorenzo, Ferreira & Ratti, 2013; Kahrik, Novák, Temelová, Kadarik & Tammaru, 2015; Novák & Temelová, 2012; Sevtsuk & Ratti, 2010; Monsivais, Ghosh, Bhattacharya, Dunbar & Kaski, 2017).

In addition to mobile operators' data, data from Google Location (location tracking) is also valuable. Google collects this data under specific terms of conditions and only if a Google Maps user agrees to share their location. Compared to the data of mobile operators, data from Google Location is usually more accurate, because the location of the device (most often a mobile phone) is determined not only by the proximity of nearby BTSs (base transceiver station) but also by connection to WiFi networks and especially by GPS (if this option is enabled on the device). Thanks to this, it is possible to evaluate in which vehicle the person was moving, whether he was static in one location and what was the accuracy of the targeted position. Google mainly uses the data for its internal analyses, however, each user has the opportunity to download their data in JSON format and further process and visualize it. Based on such data, it is possible to identify the user's location much more accurately, which is crucial for subsequent analyzes. The data can be used, for example, to identify the most common routes (Löchtefeld, 2019), to analyze population movements (Ruktanonchai, Ruktanonchai, Floyd & Tatem 2018), to evaluate spatial patterns of movement, or to analyze visit rates of various places (Romero, 2019). Also, on 3 April 2020, Google released a new service, COVID-19 Community Mobility Reports (Google LLC, 2020), in response to requests from official institutions to provide at least anonymized data and the behaviour of Google Location users (this involves the conscious provision of information on the position of a mobile device based on GPS and device registration in the mobile network). This dataset has already been used by the authors (Pászto, Burian & Macků, 2020) to evaluate COVID-19 pandemic impacts on human behavior. It should be added that Apple has published similar data from its users (Mobility Trends Reports), which, however, focus more on navigation data and vehicle use. The extent of the COVID-19 pandemic threat even induced Google and Apple companies for partnership in the common project on contact tracing technology.

In this article, as a showcase, the authors conducted an individual case study about their personal Google Locations data (from Google Timelines) to explore how authors changed their daily habits within the Olomouc city (Czechia) during the pandemic. The main research goal was to reveal if (and to what extent) COVID-19 affected authors mobility from the spatial perspective by revealing a geographical pattern of the activities before and during the pandemic. In this article, authors describe data acquisition, methods of spatial statistics applied as well as results and their implications. The results show how COVID-19 restrictions had different effects on the intensity of authors' daily mobility, which closely relates to their individual work-life customs. This contribution also manifests possible usability of localized mobility data, if available at least at aggregate levels, within the e-planning agenda of municipalities.

2. DATA AND METHODS

Compared to the standard cell phone location data, Google Location data is qualitatively significantly better, especially concerning location accuracy. The location is based not only on interpolation from BTS stations but on other location techniques, like GPS, WiFi, etc. Personal authors' data from the Google Location service was used for a detailed analysis of their spatial behavior change. In general, the data can be downloaded by any user for the entire period when using this service. For a certain level of anonymization, the data was generalized and are referred to as persons A, B and C. First, the data was downloaded in JSON format and was converted by a freely available script (Boates, 2019) to GeoJSON format. Then, the data was processed into the geodatabase environment (Esri File Geodatabase). Due to the large volume and time range of data (for one of the monitored persons up to the last five years), it was necessary to adjust collected data sets. First, the basic data filtering, elimination of locational errors and selection of the time-period for subsequent analysis was done. Two time-periods were studied in detail: 1) the period from 1 February 2020 to 10 March 2020 and 2) the period from 11 March to 18 April 2020. The first period of five weeks represents the situation with no restrictions in the Czechia. It represents the period with standard behavior of observed persons. On 12 March 2020, the Czech government declared the state of emergency with strict regulations for schools that were closed immediately. The following period, therefore, represents a state when a significant change in the behavior of the authors of the article could be expected.

The data was processed using several spatial methods, which allow various identification of changes in behavior between the two periods. These changes can be monitored by different spatial patterns. For this purpose, the data were aggregated into a hexagonal network in the ArcGIS environment and further processed using hot spot analysis, kernel density analysis (heat maps) and using a modified kernel density method, which allows aggregation of points into hexagons taking into account the influence of neighboring cells. Each author defined the most frequent points of interest (residence, workplace, shopping and leisure - only indoor activities) for more accurate quantification of changes. Buffers with a radius of 300 meters were generated around these points and the difference in the number of recorded position points within the circles between the first and the second monitored period was evaluated. The radius was chosen concerning the positional accuracy of the input data. Results of the analyses were presented by several geovisualization techniques.

3. PERSONALISED ANALYSES OF GOOGLE LOCATION DATA

The following description focuses on selected aspects of changes in the behavior of the monitored persons to point out a very detailed evaluation of changes. Unlike studies that work with anonymized and aggregated data, it is possible to conduct the interpretation at a very concrete and detailed level. The findings below correspond very well to the general and expected trends, nevertheless, it is a unique method of evaluating data. The procedure shows not only the possibilities but also the risks of using (and possible misuse) of this type of data.

The visualization of all recorded points (Figure 1, 2, and 3) shows a significant change in the spatial distribution between two observed periods. A significant change in the range of motion is evident in all subjects. While in the first period the spatial distribution of points occurs across Europe (shown in Figure 1), there is a significantly smaller spatial distribution of activities in the second period. This fact is obvious due to the pan-European border closures on one hand, but on the other,

Figure 1. Movement locations of all three persons at international (top), regional (middle), and city-level (bottom) before and during COVID-19 pandemic

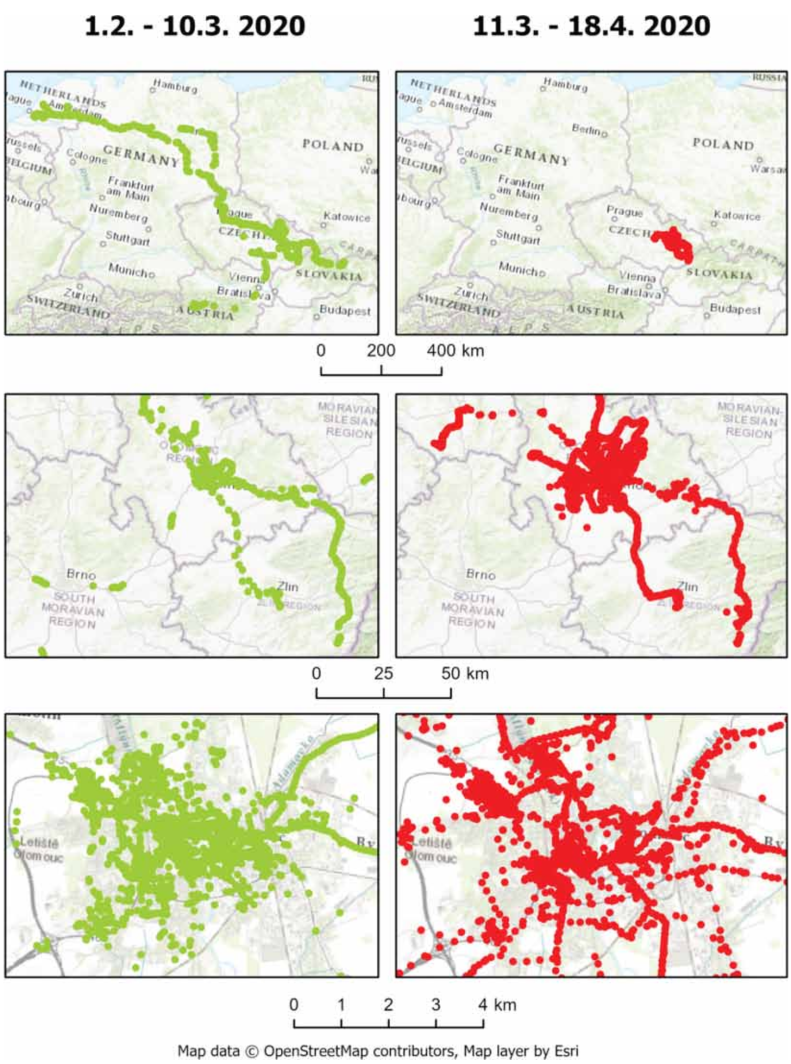
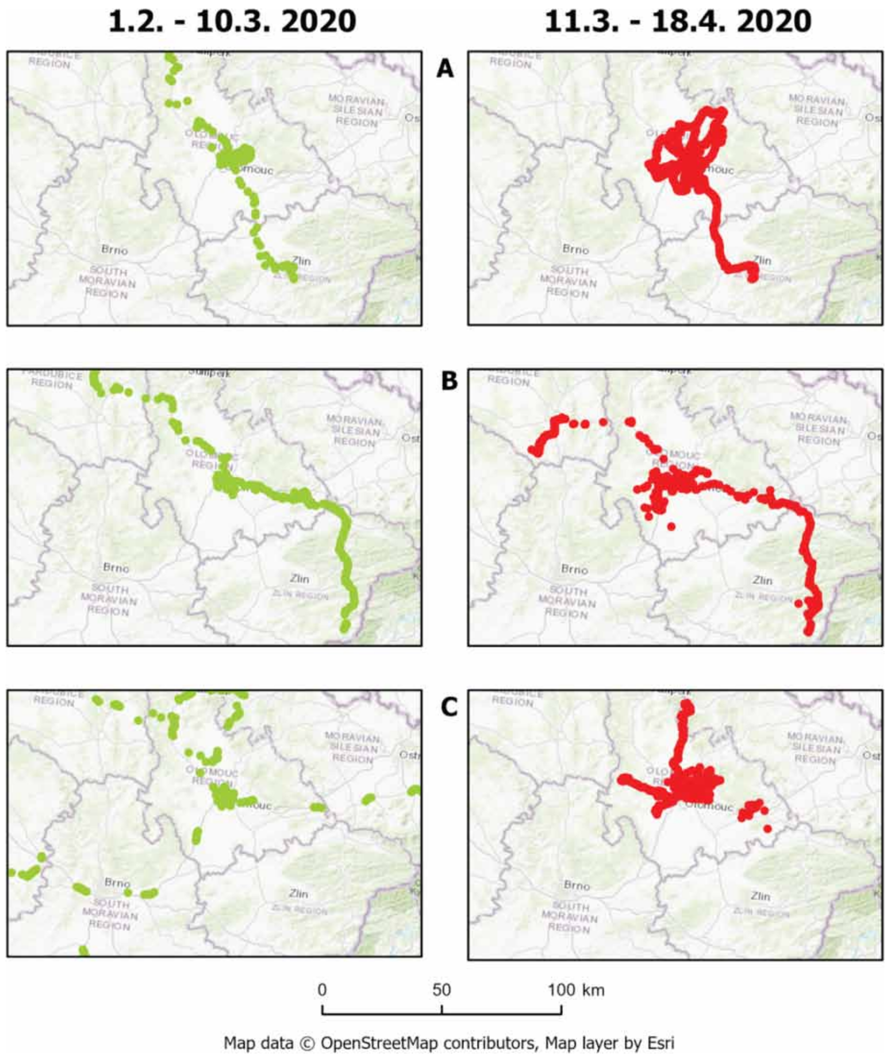


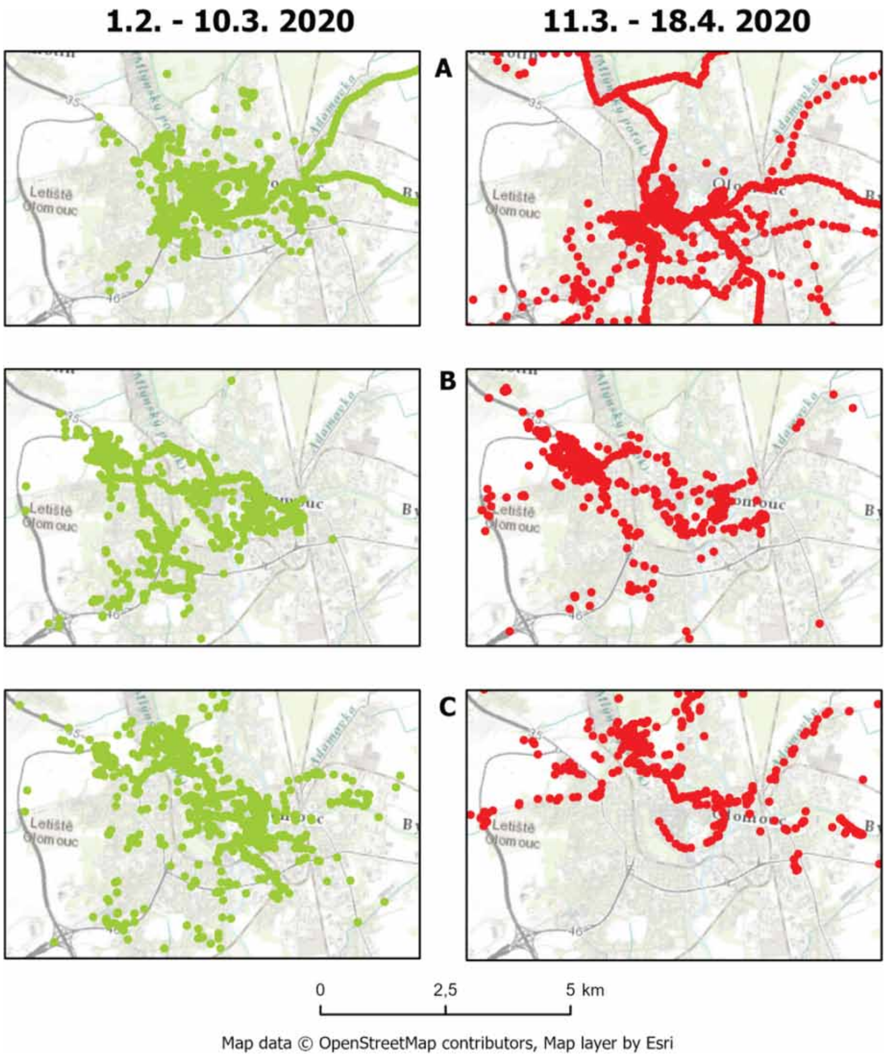
Figure 2. Movement locations of persons A, B and C at the regional level



such visualization demonstrates the real personal effects of COVID-19 impact. The situation is slightly different when evaluating movement within the city of Olomouc and its surroundings (Figure 2 and 3). Although there is a noticeable change in the spatial distribution of points (e.g. complete elimination of points in the southern part of the city for person C), some new localities occur - these are mainly recreational places in adjacent parks, forests, protected areas, hiking trails and bike paths. This situation very well documents the established restrictions, which, however, did not affect outdoor recreational and personal sports activities (as it was allowed to visit outdoor spaces during the state of emergency and restrictions on free movement in Czechia).

At the regional level (Figure 2), the COVID-19 related restrictions did not have much significant impact on observed persons' movement. It might be due to the fact that inter-regional travels were not banned in Czechia (although public transport services were dramatically reduced). However, it is visible how the usual behavior of all persons changed (maybe except person B). Persons A and B remained their travels to the southeast as these are locations of their families (parents), while person C

Figure 3. Location of persons A, B and C at the city level



reduced even family visits and spend his time in Olomouc and close surroundings. All three persons, however, increased their occurrence in the city outskirts with natural land-use.

Especially in the most spatial detail (Figure 3), it is clear how the behavior pattern changed for every person differently. While person C (mentioned earlier) eliminated his movement in the southern part of the city, person B reduced his frequency of movement, however, visited locations almost stayed the same. It is also clear from the visualizations, that the person A used his time for sports activities, which are indicated by the concentric lines (or dense points to be precise) along municipal bike trails (see Figure 2 and 3).

While the above-described results show "just" all recorded data (all points recorded by Google Location service), the following results show the data aggregated using several methods. Each method has its advantages and disadvantages and highlights to slightly different aspects of changes in the behavior of the subjects. Figure 4 shows data aggregated into a regular hexagonal network (approx. 35,000 square meters, with an edge length of approx. 115 meters). The shape and size of hexagons have been tested many times in the past and evaluated for many reasons as the most suitable for aggregation of point data (for more details e.g. Birch, Oom & Beecham, 2007; Burian, Stachová & Vondráková, 2018).

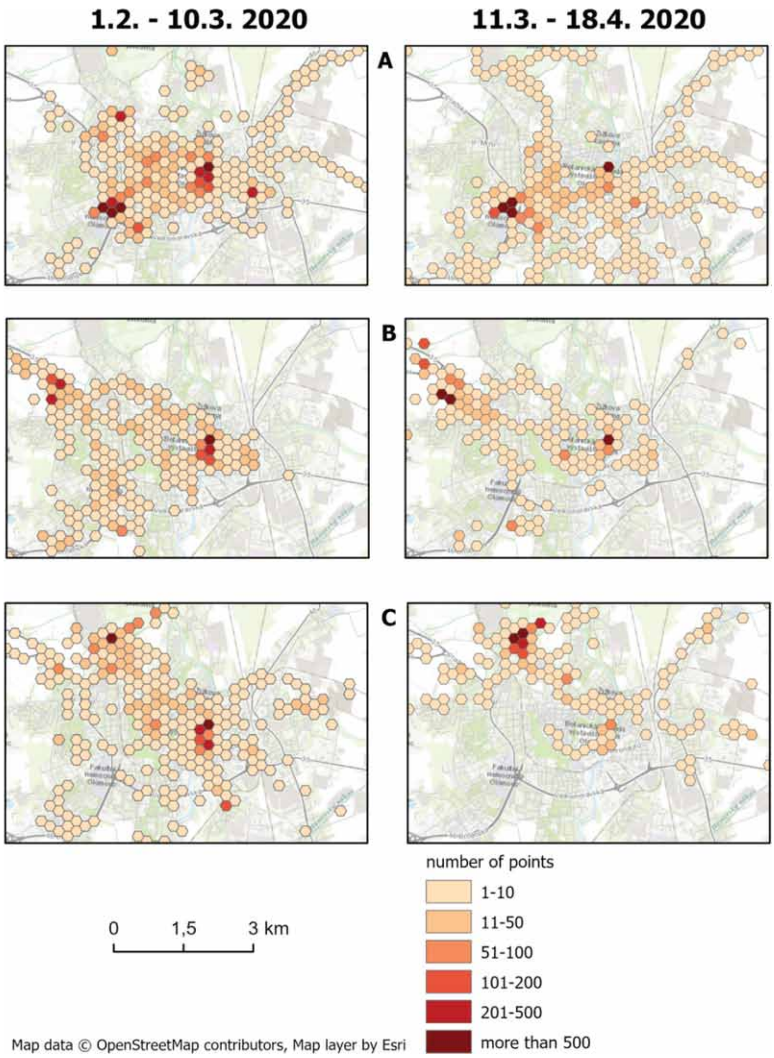
All three monitored persons are academic staff, working in the city center (Figure 4 and 5), while persons B and C have two jobs and therefore occur in two workplaces. Person C has frequent business trips to the historic city center, so his third location related to work activities is located in the city (best visible in Figure 8). Other selected points of interest (residence, shopping and leisure) are spread throughout the city. Person A has a residence located in the southwestern part of the city, there is also the most frequent shop nearby and three places of entertainment are spread throughout the city. Person B has a residence located near the most commonplace for shopping, which is within walking distance from his residential area. The swimming pool is mentioned as a point of entertainment for person B, but it was visited less often in both monitored periods. Person C has a residence located in the north-western part of the city, entertainment centers in the eastern part and a total of 4 most frequent shops are shown as the most frequent shopping places.

A high concentration of the number of workplace and residence points is visible, while a significant decrease in activity at the workplace was observed for all persons. This is confirmed not only by the absolute number of points in the given localities (Figure 4) but also by their visualization using the kernel density method aggregating the output to the hexagonal network (Figure 5) and also by the kernel density method displayed in the form of a heat map (Figure 6). This decrease is most significant for person C, who occurred at the workplace only once in the second observed period (during the peak of COVID-19 pandemic) and extended the temporal and spatial pattern of his occurrence in his area of residence (including family walks or outdoor sports around living place). The activity of person B decreased too, but not so much as person C. This is caused due to different family situation (alternating care for a small child) of person B that influenced the frequency of his visit to the workplace. In all cases, however, there is a very significant decrease in workplace occurrence, which can be demonstrated by the result of hot spot analysis (Figure 7). The hot spot analysis allowed eliminating workplaces from the visualization of the second period for all three persons (unlike e.g. kernel density in Figure 5 or 6).

Similar findings are evident from the occurrence intensity maps (Figure 6), processed in the Location History Visualizer application. This form of data visualization is very intuitive, but partially distorting. Input data are underestimated in places with a very high density of points, and in contrary, places with a very low incidence are slightly overestimated. In contrast to the commonly used methods of kernel density estimation in the GIS environment, the results are slightly skewed, due to displaying areas that are not statistically significant. On the other hand, this method of processing suppresses very dominant places of work and residence and enables better evaluation of other spatial patterns of occurrence of persons.

The last type of data processing and visualization is shown in Figure 8 and in Table 1. The number of points displays the most frequent places of occurrence of monitored persons in selected categories that fall within a distance of three hundred meters. In the case of person B, this size is reduced to 200 meters at the place of residence and shopping so that the two circles do not overlap and the results are not distorted. The difference between individual localities in two monitored periods is always assessed, so the change in the size of the circle does not affect the results in any way. The map in Figure 8 and Table 1 shows a significant increase in the incidence at the place of residence (up to hundreds of per cents) and a significant decrease in the incidence at the workplace. In both cases, however, there is a significant difference between persons A and C and person B. Person B has a significantly lower increase in incidence at the place of residence and at the same time a significantly lower decrease in incidence at the place of work. This is mainly due to different working conditions at the place of residence (home-office). In contrast, both person A and person C show a very similar decrease in incidence at the workplace and a similar increase in incidence at the place of residence. For all monitored persons, there is a relatively balanced decrease in the occurrence in shopping centers and a very significant and balanced decrease in the occurrence in places of entertainment and leisure (one

Figure 4. Aggregated location of person A, B and C

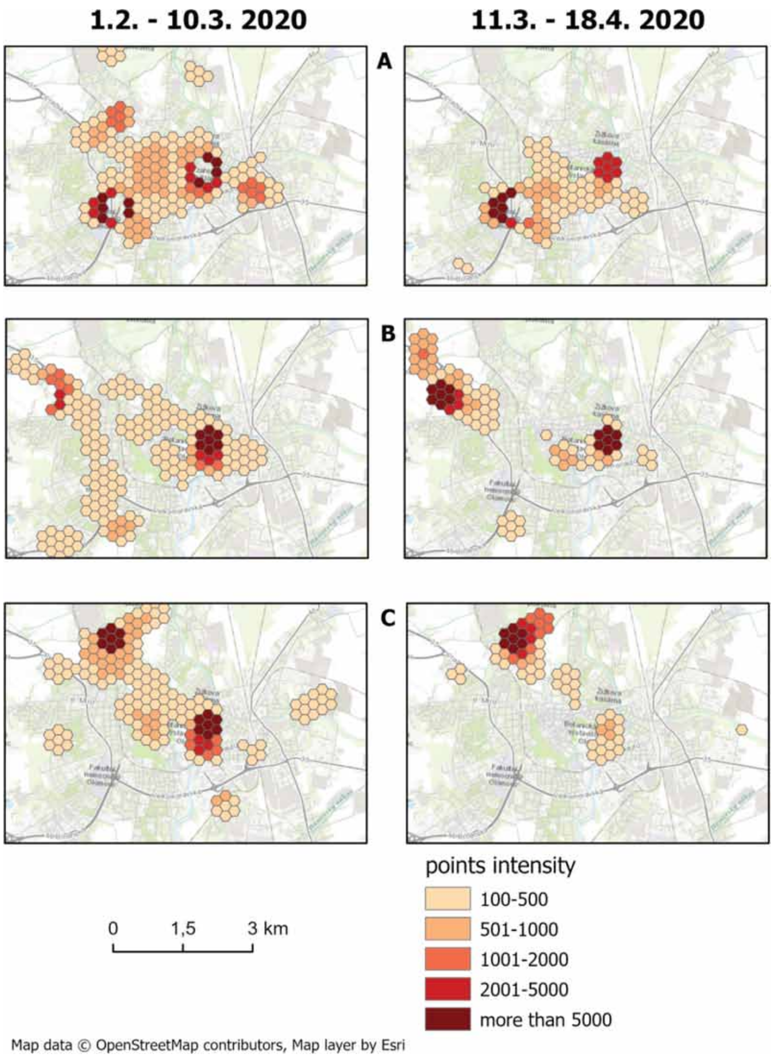


hundred per cent decrease). However, this figure does not affect a very significant increase in the occurrence in natural sites, which is evident especially from Figure 3 and partly also from Figure 2.

4. DISCUSSION

In the developed countries, ownership of a mobile phone is taken for granted, and therefore the location data can serve as the best source for identifying the true location of the population over time and space. The problem with these data, however, is their unavailability, whether due to price, incompleteness, or other objective criteria. However, when looking at cell phone ownership from the opposite perspective, the limiting factor can be considered that we do not have data on people who do not own a cell phone (and can often be marginalized groups in society such as the homeless people or people affected by social or economic deprivation).

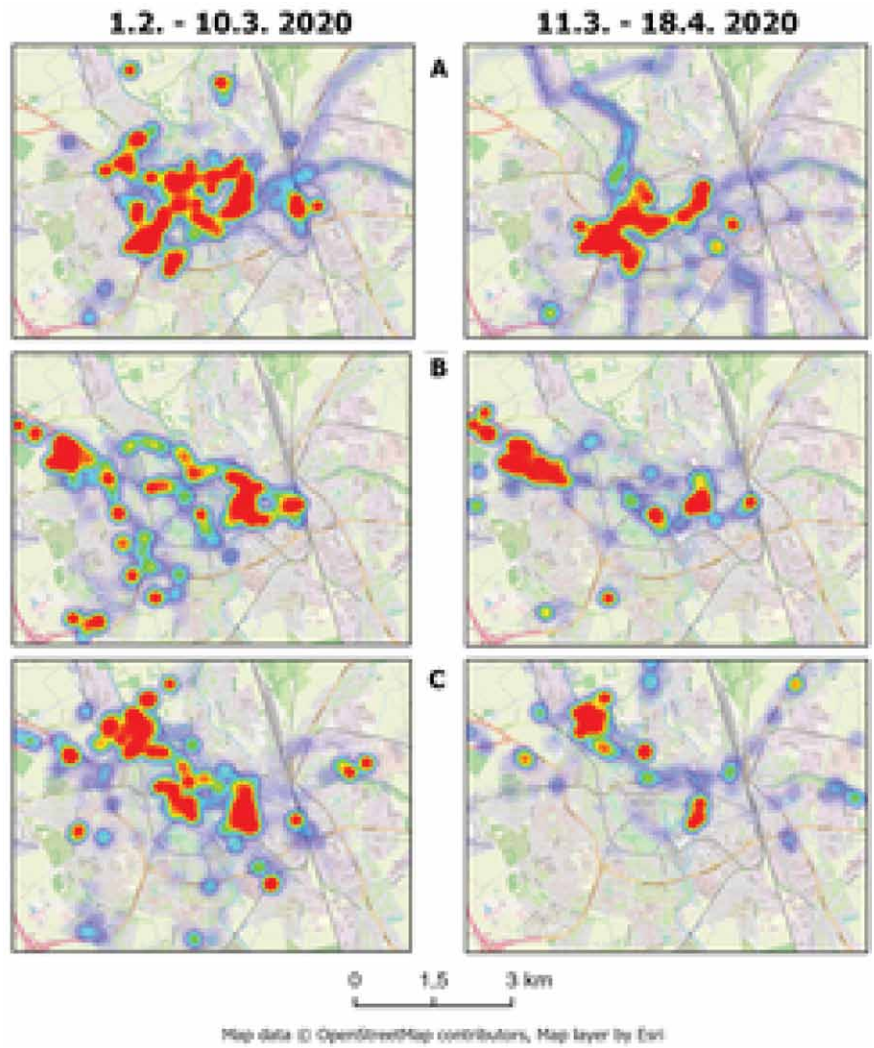
Figure 5. The intensity of location of person A, B and C analyzed by kernel density method and aggregation into the hexagonal network



The results of our analyses are influenced by the accuracy of positioning using BTS stations or GPS. Much of the input data from Google Location is burdened with some errors, so relatively complex filtering and validity processing were required. Part of the displayed data is affected by incorrect or inaccurate positioning, for example, due to a lower number of visible BTS stations, and thus a lower level of position accuracy. We believe that even so, the results (especially within the city) are very credible and relevant.

The above-mentioned analyses and their interpretations accurately and reliably describe the actual behavior of the monitored persons. In contrast to the usual approaches to the collection of data on population movement, this is an example of a very personalized approach that allows retrospective spatial-temporal analyzes suitable for the identification of spatial patterns and changes in mobility and other behavior of persons. Although this is very sensitive data of a personal nature, in the case of their anonymization and at least partial aggregation, it could be an important and qualitatively valuable source of information in the future.

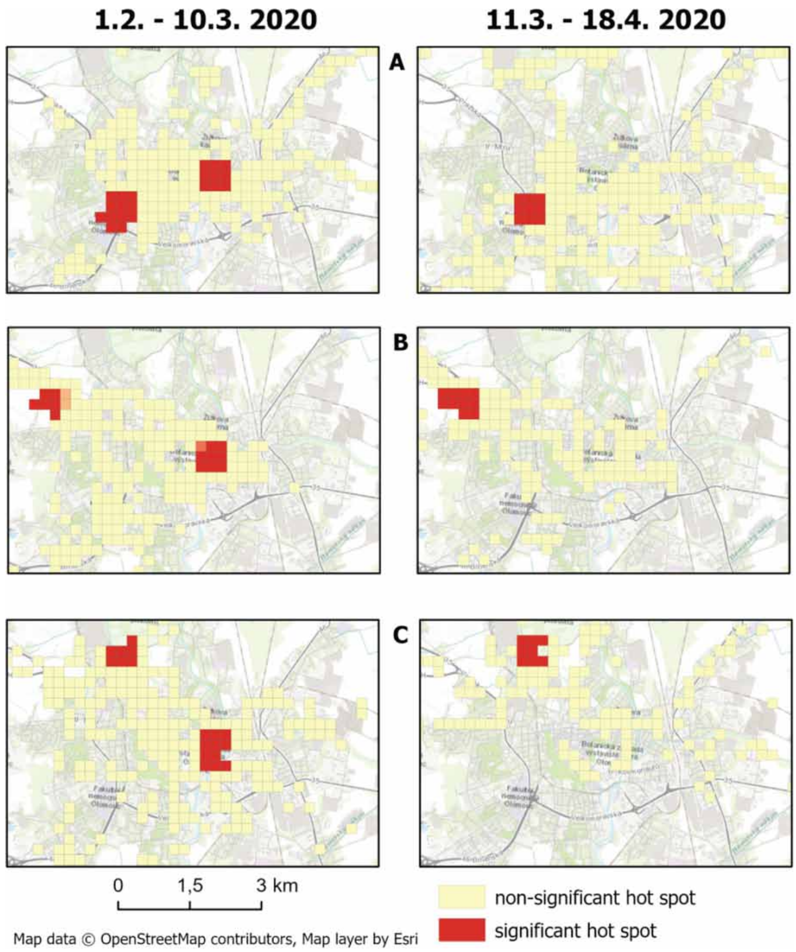
Figure 6. Occurrence intensity of person A, B and C by kernel density analyses



5. CONCLUSION

The use of detailed and individual data from Google Location service for the analysis and evaluation of user behavior in a crisis of the COVID-19 pandemic is a very unique approach that has not been published anywhere yet. The authors are fully aware that this data shows a lot of other information about the spatial behavior of authors and due to personal nature of such datasets, it is very important to balance between data protection and data usability. At the same time, however, the authors think it is beneficial to show how to process and use individual data. The current situation in the world clearly shows that positional and individual data represent a way out from the crisis until the vaccination is not available, as such data could be included in concepts of smart quarantine or infection-carriers backtracking. It can also be useful in the case of a pandemic or any other situation where the safety and health of the population are concerned.

Figure 7. Significant and non-significant occurrence hot-spots of person A, B and C



However, it is necessary to approach this data very sensitively and to pay close attention to the protection of personal data.

Albeit the spatial trend of mobility/behavior changes of monitored persons might appear obvious, the situation caused by the COVID-19 have never been experienced in the modern history of Europe, let alone the Czechia. In this sense, the article brings not only capture of real individual changes of behavior and daily-habits of the authors through their location data, but also a variety of map visualizations, how such data can be treated and analyzed. In a broader perspective, Google Location datasets and other similar location-based services could be exploited for general (spatial) planning purposes of cities. As mentioned earlier, personal and data privacy remains the biggest issue or obstacle in this sense. Therefore, various levels of data aggregation and generalization should be applied.

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Figure 8. Aggregated location of person A, B and C into areas with highest occurrence intensity

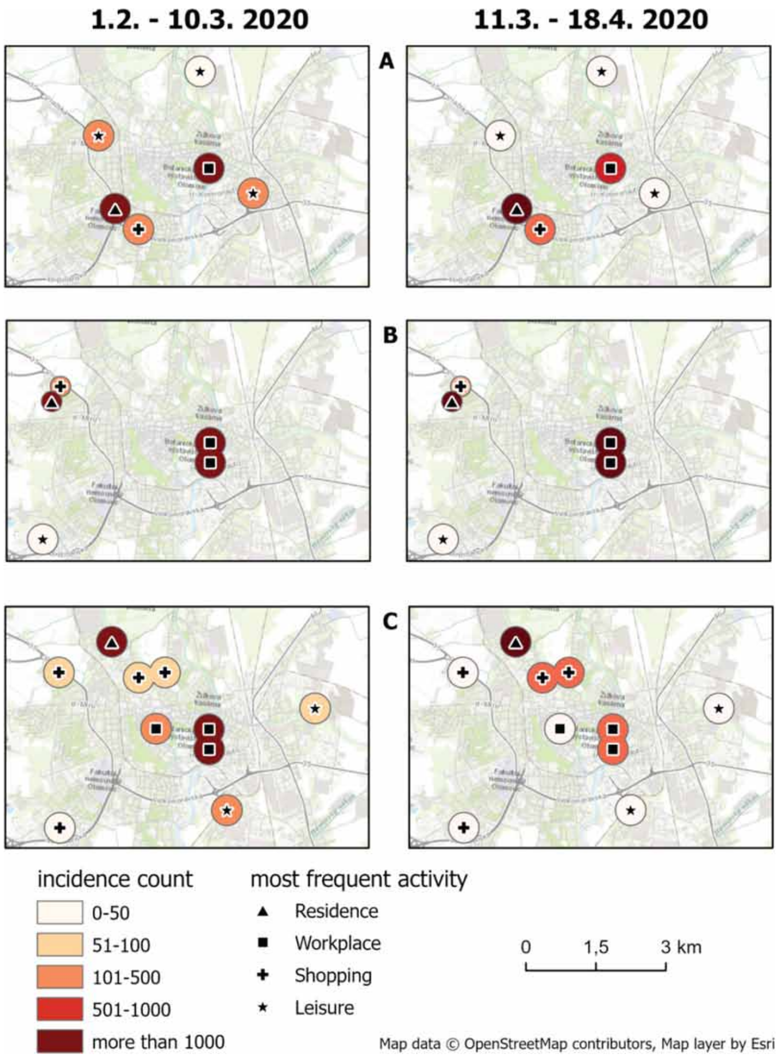

Table 1. Change of occurrence intensity of person A, B and C in selected areas

Category	Change of Occurrence Intensity [%]		
	Person A	Person B	Person C
Residence	638	80	748
Shopping	-29	-75	-20
Leisure	-99	-100	-100
Workplace	-82	-36	-93

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