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Entry

Application of Mobile Operators' Data in Modern Geographical Research

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Definition: Mobile operators' data are one type of Big Data. These are any data about events related to the use of a mobile phone. These data include subscriber identifiers and associated time and location attributes. Big Data in general usually includes datasets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process data within a tolerable elapsed time. Big Data can be described by the following key characteristics: volume, variety, velocity, veracity, value, variability etc. Mobile operators' data are supplied by the Mobile Network Operators. The main distinguishing features of the operator are, firstly, the possession of a state license to use the radio frequency spectrum, and, secondly, the possession or control over the elements of the network infrastructure necessary to provide services to subscribers in the authorized radio frequency spectrum. The smallest structural territorial element for cellular communication systems is a cell; its dimensions can be different (250 by 250 m, 500 by 500 m, etc.).

Keywords: mobile operators' data; statistical data; population; settlement system; migration; transport modeling; monitoring of socio-economic processes; strategic planning; delimitation of agglomerations; natural and man-made risks

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1. Introduction

The flows of people, vehicles, and information are the most important components of the modern society life. At the same time, collection and analysis of data on these flows using traditional methods of social science research becomes more and more difficult every year. The need for a high degree of localization and temporal fragmentation of information makes official statistics unusable for analyzing a significant number of socio-economic processes. It becomes evident that in order to overcome the existing statistical barriers, it is necessary to use alternative information resources. These include data from satellite images, social networks, Internet web pages, bankcard transactions, mobile phones, and other sources, collectively referred to as "Big Data".

In 2008, the American scientist D. Hellerstein described the appearance of "Big Data" as a kind of "industrial data revolution" [1]. Indeed, the 21st century marked a real technological revolution in the field of obtaining and analyzing information: the appearance of fundamentally new data sources, improvement of their processing methods, and the widespread introduction into research practice. All this provided scientists with great opportunities to supplement and expand knowledge based on traditional statistics.

A special place in the extensive list of possible Big Data resources is occupied by mobile operators' data, which in recent years have become one of the most promising sources of additional statistical information. According to the figurative expression of Professor A. Pentland from the Massachusetts Institute of Technology, mobile operators' data are "digital breadcrumbs" that clearly mark the ways people move in space [2]. In government, academia, and the business communities, mobile operators' data are expected to fill gaps in official statistics.

The International Telecommunication Union (ITU) report for 2014 states that the average mobile penetration rate is 96.4 per 100 inhabitants worldwide, while in Russia, this figure reached 99.7 per 100 inhabitants [3]. Almost every person in the world lives within range of a mobile cellular signal. These figures demonstrate the widespread penetration of mobile communications into modern society, and determine the high representativeness of the data, based on almost 100% of the sample. Moreover, the report notes that this source of information is particularly relevant for developing countries, as well as countries that have problems with the collection of statistical information [3,4].

2. Geography of Mobile Operators' Data Application

Recently, mobile operators' data have occupied their information and statistical niche in the resource base of many government and international organizations, scientific, and business communities. The countries that are advanced in the use of mobile operators' data are the USA, Great Britain, France, Belgium, and Estonia. Estonia, due to its small size, high level of society informatization, and rich scientific traditions in working with Big Data, is a unique "experimental laboratory" for conducting various kinds of research in this area. Additionally, it is necessary to highlight Russia, Germany, Italy, Spain, Portugal, Czech Republic, Austria, Switzerland, Sweden, Japan, China, and Israel. Thus, most of the research is concentrated in Europe, the USA, and a few Asian countries. Figure 1 shows research activity based on mobile operators' data and key national priorities in the use of this specific information.

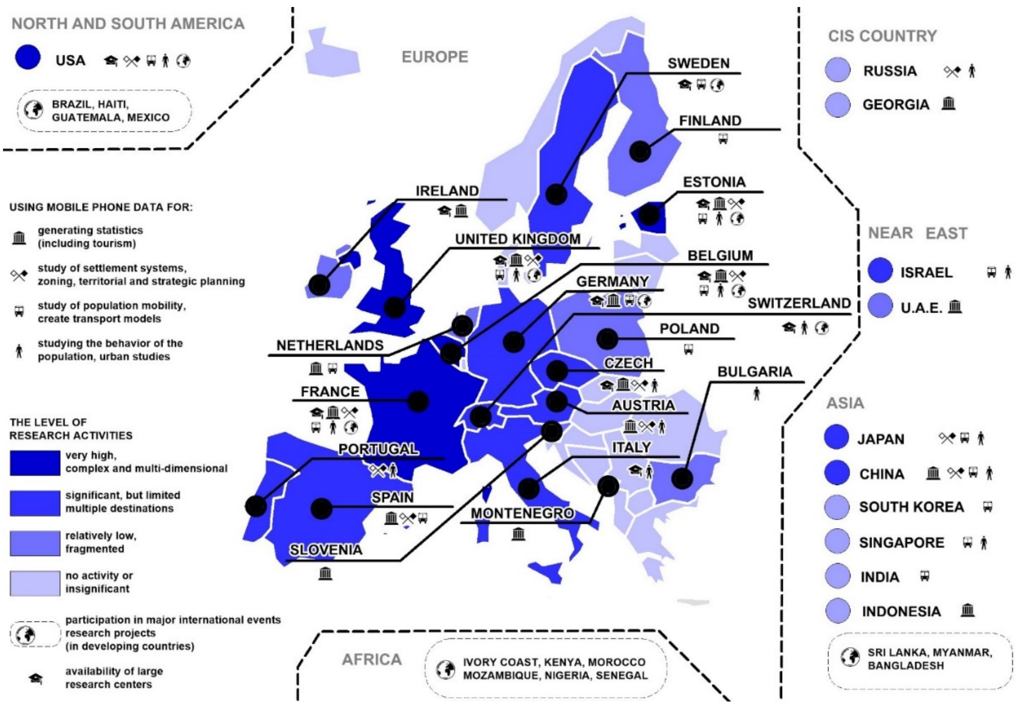

Figure 1. Geography of mobile operators' data application. Source: [5].

In pragmatic terms, there are several key areas of research based on mobile operators' data (Figure 1):

- creation of statistical databases;
- study of settlement systems, zoning, territorial and strategic planning;
- study of population mobility and construction of transport models;
- study of population behavior and urban studies.

3. Advantages and Disadvantages

In the context of the growing interest in "Big Data", it is necessary to realize their relevance and reliability. The strengths, weaknesses, opportunities, and threats of this type of data are presented in the SWOT analysis (Table 1).

Table 1. SWOT analysis of mobile operators' data in relation to geographical research.

Strengths	Weaknesses
• a high degree of conformity with reality in time and space; • no connection to the administrative-territorial division; • possibility of using in different spatial scales and time intervals; • almost complete coverage of the population; • high density of time slices of registration; • good connection with other types of "Big Data"; • significant opportunities for visualization	• non-personalized nature; • underestimation of persons without mobile phones (children, infants, etc.); • superficial nature (lack of information about the user, motives and purposes of his movements); • problems with storage, processing, and analysis methods (the need to use large amounts of memory, develop specialized software, etc.); • technical "noises"; • the impossibility of long-time series constructing (more than 5 years) due to the novelty of this data type; • legal and regulatory limitations on use
Opportunities	**Threats**
• overcoming of statistical gaps for territories with a lack of high-quality statistics; • simplification of interdepartmental comparisons; • development of new statistical indicators reflecting the characteristics of the settlement dynamics; • technological possibilities of data cleaning and calibrating to improve their accuracy; • applicability of data for real-time monitoring and problem-solving; • comparability and integrability with other data sources (traditional statistics, satellite imagery data, etc.)	• the issues of data privacy and security; • "digital gap" and "asymmetry of information" between people with access to data and other citizens; • public distrust; • resistance from data providers and holders

As shown in Table 1, along with undeniable advantages, mobile operators' data have a number of significant weaknesses. The issue of the accuracy of mobile operators' data, like any other source of network data, is a serious methodological problem. Obviously, information from mobile phones cannot be presented as completely reliable, since it has its own immanent limitations that distort reality.

The main weakness of mobile operators' data is their non-personalized nature, as well as the related problem of accounting for people who do not have mobile phones or have devices registered to other persons (for example, relatives). In addition, there is an underestimation of SIM cards from other operators and disabled devices. A separate problem is technical interference-associated, for instance, with the overlap of signals from neighboring repeaters [6]. Calibration helps to solve some of these problems, but it is impossible to completely clear and update the data array. Given the novelty of this information source, another significant weakness is the impossibility of "long" time series constructing. This may be important in cases of assessing long-term socio-economic transformations of territories. In terms of introducing of mobile operators' data into scientific use, one cannot fail to mention the relative high cost of this information source.

At the same time, a number of researchers noted that the "scale effect" (i.e., almost 100% sample) significantly reduces the cost of mobile operators' data per respondent compared to the population census or sociological surveys [7]. Another weakness of mobile operators' data is the difficulty in obtaining data from several holders, which significantly increases the cost of information and may reduce its quality. Due to the linking of data to personal information of citizens, there are also legal and regulatory restrictions on their use.

One of the threats to the use of mobile operators' data is the possible problem with the security of subscribers' confidential information, as well as the problem associated with the "asymmetry of information" between people with access to data and other citizens [8]. The threat to the personal data security is the main obstacle to the introduction of mobile operators' data into practical and research use in many developed countries. The danger of "digital gap" that allows one part of society to use the benefits of better awareness for its own commercial or political purposes, in modern realities also makes certain difficulties for the use of mobile operators' data.

However, the main advantage of mobile operators' data is their exceptional ability to capture spatio-temporal changes in the "real time" with almost 100% population coverage and appropriate calibration. This gives the right to consider them as close to reality as possible [9,10].

4. Obtaining the Data

4.1. Positioning Techniques

Mobile operators' data are firstly about positioning. There are quite a lot positioning systems today, but most of them do not provide feedback to the operator. The mechanics of cellular communication are indeed based on data exchange between subscribers and operator. Data exchange is a key component of getting position of subscribers.

In a simple radar model, we can get the position of an object knowing the coordinates of several basic radar stations. The math is quite simple—geodesic triangulation method. In our case, with cellular phones, we do not have radars, but phones periodically transmit data to nearest stations and analyzing the signals, we can derive position. Analyzing the signal strength from subscriber with application of suitable algorithms is another approach to positioning.

The most commonly used technology is LBS—location-based service—illustrated by Figure 2.

It takes several techniques, cell identity, timing advance, and signal strength, to get the optimum positioning performance [11].

Cell identity technology is based on the idea that mobile stations serve only a restricted amount of area. Thus, if the subscriber's phone is being used by a certain station, it is in the area of service. The accuracy is not high in that case, so another two technologies are applied.

Timing advance originally was involved as a technical parameter for mobile station operation and due to its specification can be used to estimate distance between serving station and subscriber. In any way, it can estimate only a ring segment from serving area and positioning is still not accurate.

Signal strength is estimated by complex models which includes specification of geographic area, number of neighborhood stations, and so on.

The accuracy of the LBS method varies from hundreds of meters to a thousand, depending on the density of the cellular stations. Therefore, we have maximum accuracy in the cities, and it is noticeably reduced in less populated areas [12].

Thus, what is the volume of obtained data we can get? As an example, let us look at Table 2. The database includes depersonalized positions in 500 squares meters cells of subscribers in Moscow region of Russia with a time-lapse of 30 min for one year. The number of cells is 190,200.

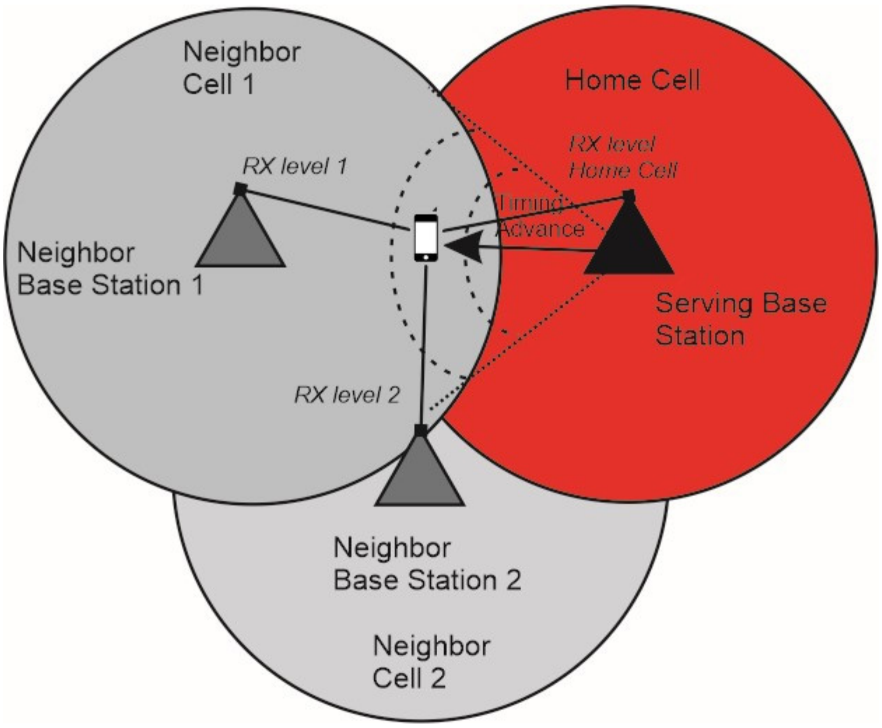

Figure 2. Localization by referring to cell identity, timing advance, and signal strength.

Table 2. Characteristics of the primary mobile operator's database for Moscow region of Russia.

File Name	Time Period	Number of Rows of SQL Database Tables	SQL Database File Size, GB
02_CDensity_1_201901	19 January	3,160,471,757	167
02_CDensity_1_201902	19 February	3,348,306,368	191
02_CDensity_1_201903	19 March	3,708,434,300	196
02_CDensity_1_201904	19 April	3,830,636,603	202
02_CDensity_1_201905	19 May	4,200,882,887	222
02_CDensity_1_201906	19 June	4,052,681,497	214
02_CDensity_1_201907	19 July	3,965,982,117	210
02_CDensity_1_201908	19 August	3,926,705,856	211
02_CDensity_1_201909	19 September	3,804,966,868	204
02_CDensity_1_201910	19 October	3,831,124,135	202
02_CDensity_1_201911	19 November	3,532,897,684	187
02_CDensity_1_201912	19 December	3,160,471,757	167
02_CDensity_1_202001	20 January	3,162,226,751	194
Sum	13 months	47,685,788,580	2567

Source: [13].

The raw data size is 2.5 terabytes and the number of rows in the table is about 10^{10}, a really big amount of data which requires special methodology to be applied such as parallel computing and specifically configured database servers.

4.2. Security and Privacy Issues

The security and privacy of personal data in cellular network are regulated by legislation of countries/regions. The mobile operator is responsible for storing and handle private data securely. There is a variety of data depersonalization algorithms, when we speak about LBS data transfer from operator to researcher [14]:

- method of identifiers implementation,
- method of change of composition or semantic,
- method of decomposition,
- mixing method.

As an example, let us consider Figure 3. In this case, the initial personal identifiers of subscribers (names, phone numbers etc.) are replaced with alternative ID (numerical code) according to rule *f*. The table of conformity is known only for mobile operator and should be securely handled as any personal data. The researcher gets only the alternative ID for the LBS database. Moreover, the conformity table can be erased by operator for the reason of personal data security, so it becomes impossible to restore relations *f* between artificial and personal ID in data. Along with artificial ID, different aggregation of data can be used. For example, subscribers in certain area can be summarized to get the indicator of total population of the area.

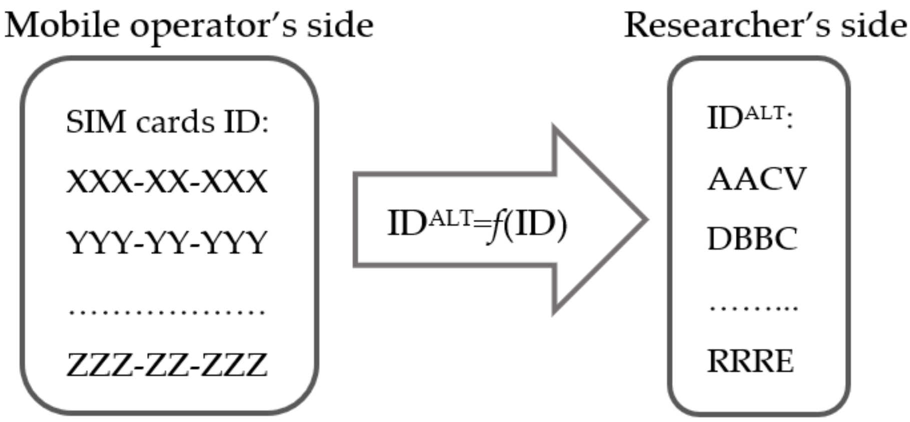

Figure 3. Depersonalization of cellular data by implementing artificial ID. Source: compiled by the author.

Obviously, the risk of data theft cannot be completely excluded, as with any services using personal data.

5. Methodology and Algorithms

There are two main points when we speak about methodology and algorithms for mobile operator's data:

- storing the data, primary processing, and so on;
- data analysis, statistical modeling, and mathematical models' calibration.

The first point is all about database technologies such as SQL and no-SQL: Hadoop, Azure, MongoDB etc.

Due to the nature of mobile operator' data as a Big Data, a huge amount of data science algorithms is applied for analysis and modeling. Data anomaly detection [15], clustering [13,16], and Markov chains models [17] are widely used.

Cellular data are used for agent-based models' calibration (see WU, etc., 2019). The spatial-temporal nature of data is used in spatial econometric models [18,19].

6. Practical Application of Mobile Operators' Data

6.1. Using the Mobile Operators' Data to Generate Statistics

Mobile operators' data are increasingly used in demographic statistics year by year. Traditionally, the main sources of population statistics are the census, administrative population registers, and household surveys. Databases derived from current population statistics are considered accurate and detailed, but highly static. In addition, they have large time gaps (as a rule, they are presented in annual terms), which does not allow building highly detailed time series. In this regard, the use of new alternative data sources is very important for the statistical services of many countries.

Although mobile operators' data do not provide the same accuracy and detail as the census, a comparison of these data sources shows that they are highly correlated [20]. In particular, in [10], a Spanish-French team of researchers showed that three different sources of population data (census, social networks, and mobile operators' data) provide comparable information with a correlation coefficient close to one. At the same time, mobile operators' data are more correlated with the census than social networks data.

Due to their dynamism, mobile operators' data can make a significant contribution to the analysis of such "fast" socio-economic processes as pendulum migrations of the population. Most people spend most of their time in just a few places, so using clustering methods, the location of their home, office, recreational, and leisure facilities can be clearly identified. Results can be compared with official statistics and adjusted [21,22]. Through such comparisons, it is possible to develop a system of statistical indicators that can be generated or improved using mobile operators' data (Figure 4).

On the background of other data types, the use of mobile operators' data offers a convincing compromise: it is both highly sensitive to user movements and at the same time clearly localized in space. In addition, in methodological terms, thanks to the collection of information about subscribers' localization in "real time", mobile operators' data make it possible to realize the idea of identifying indicative points or segments of time events ("midnight", "morning start", "noon", and "length of the day", etc.) within the so-called "social time" [23].

The simplest and at the same time the most important demographic indicators that can be obtained from mobile operators' data are the size and density of the population. Since the mid-2000s, research and administrative institutions and national and international organizations have been developing methodologies for studying population density and distribution based on mobile data.

Due to specific features of the data (their high cost and low coverage), works to explore the possibilities of their use were started at the city level. One of the first initiatives to use mobile data was the Austro-American project "Graz in real time" implemented in 2005 [24]. Based on the data of Austria's largest mobile operator "A1", scientists have collected and systematized information on labor pendulum migrations and changes in the distribution of the population in Graz. A research group from the Massachusetts Institute of Technology carried out a similar project for Rome called "Rome in real time", 2012 [25].

The first economy sector that became interested in mobile operators' data to generate statistics was the tourism industry. Thus, in 2012, Eurostat commissioned a comprehensive study to assess the possibilities of using mobile operators' data to obtain information on tourist flows [26]. Since this was a pilot study, special attention was paid to identifying the strengths and weaknesses associated with the availability, relevance, and cost of data, as well as technological and methodological problems of their use.

The study notes that incoming, outgoing, roaming, and domestic data collected by mobile operators correspond quite well to the incoming, outgoing, and domestic tourism domains. At the same time, it was found that access to mobile positioning data is limited, mainly due to regulatory restrictions (related to the existing legal and regulatory differences between countries). Therefore, there is a need for a central division for national statistical offices, which will be able to accumulate multinational data in accordance with the pan-

European methodology. The result of this should be long-term, comparable, and reliable statistics on cross-country movements of citizens.

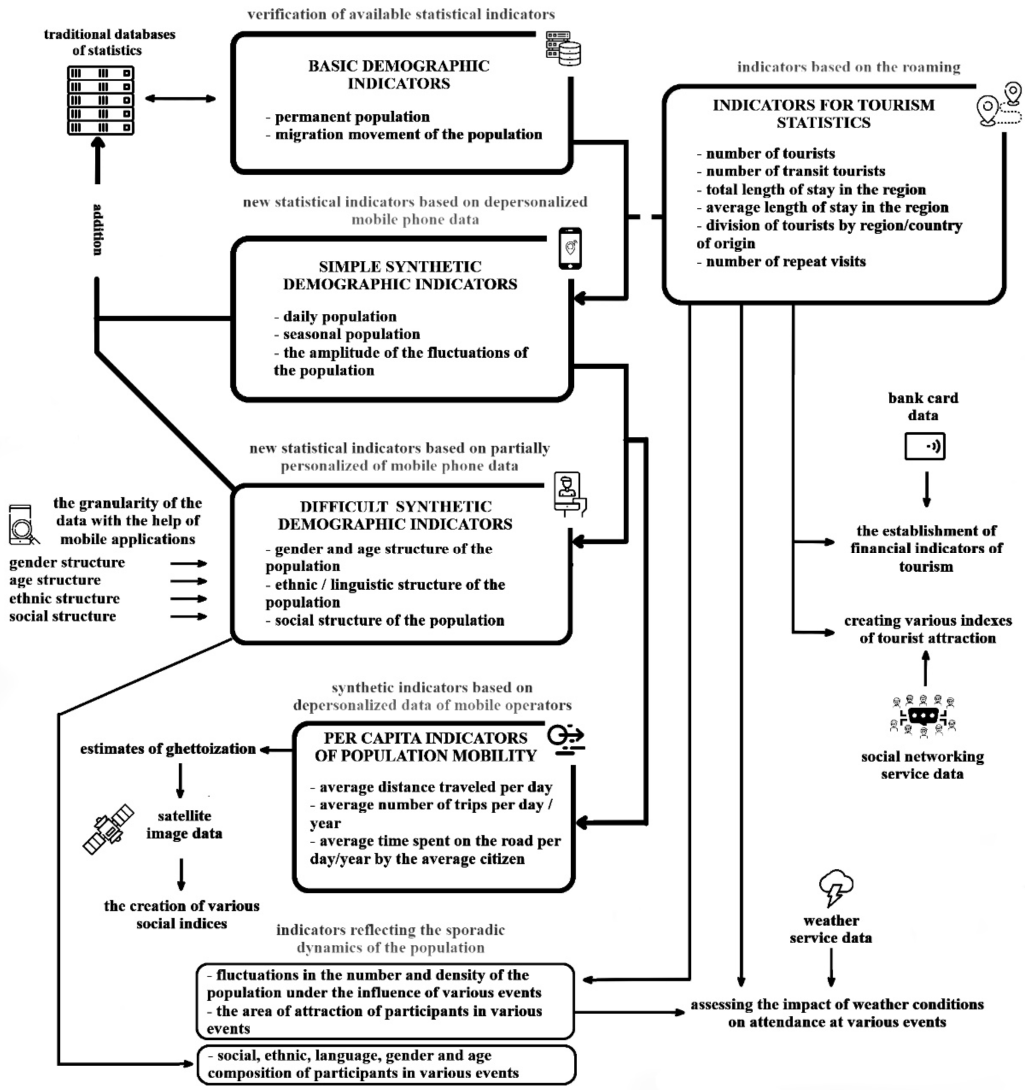

Figure 4. A promising system of statistical indicators obtained by integrating mobile operators' data into statistics. Source: compiled by the author.

The study showed that mobile operators' data could be used as an additional, but still not a substitute of, source of information for tourism indicators. In this context, the preferred option for using mobile operators' data may be to supplement existing methods with them. For instance, the collection of information in a mixed mode allows you to reduce the sample of expensive sociological surveys of tourists. Mobile operators' data allow linking digital tracks of tourists with visits to specific events and places in retrospect. This provides the development of real-time monitoring systems. In turn, monitoring, according to the experience of the so-called "tourism barometer" in Estonia, is a valuable tool for planning and managing the tourism industry [27,28].

In the Czech Republic, mobile operators' data on several dozens of highly attractive tourist destinations (UNESCO sites, mountainous areas, and spa towns) provided information on the number of visitors and their country/region. This information has been used to create development strategies and tourism marketing plans [29]. The 2010s were marked by numerous studies devoted to the study of foreign travelers and the assessment of the territories' attractiveness for international tourism in France, Germany, China, Montenegro, Japan, Indonesia, Ireland, etc.

Gradually, national initiatives in the field of integrating mobile operators' data into statistics were transformed into large supranational projects. The largest such initiative was the "ESSnet Big Data" project, launched in the European Union in 2016 [30]. Its goal is to integrate Big Data into the regular production of official statistics by experimentally exploring of the possibilities of selected information sources (including mobile operators' data). The main idea of these studies is the creation and implementation of specific experimental applications in various fields (registration of tourist flows, population mobility assessments, labor market analysis, etc.). If such applications are successful, ways of integrating prospective data into existing official statistical databases are beginning to develop.

6.2. Using the Mobile Operators' Data to Study the Settlement Systems, Zoning, Territorial, and Strategic Planning

Mobile operators' data on the return movements of the population are necessary to study settlement systems in particular agglomerations. Based on information on daily and weekly population movements, using mobile operators' data, it is possible to determine the boundaries of active interaction zones between different territories, delimit the core and suburban areas of agglomerations, and outline their boundaries. All this correlates well with existing economic approaches to the delimitation of agglomerations, which use such indicators as the volume of labor correspondence and the concentration of jobs as delimitation criteria.

A prologue to the study of agglomeration structures using mobile operators' data was the work of scientists from the University of Tartu. They studied "home-work" systems for Estonian cities and the construction of correspondence matrices on their basis [7]. A little bit later, they also developed a methodology for identifying functional areas and included mobile operators' data in approaches to identifying the structural elements of the Estonian settlement system [31].

In the Czech Republic, such studies started several years ago for territorial planning. The first successful experience of using mobile operators' data in the delimitation of Greater Prague aroused the interest of other Czech agglomerations and led to the allocation of metropolitan areas to the whole country [32]. Similar work, but with a greater emphasis on intra-urban spatial structures (in particular, the identification of mono/polycentric urban structure) was carried out by Spanish specialists for 31 cities in Spain in 2014 [33].

The study of the structural and functional profile of the territory is closely related to the analysis of daily and weekly population fluctuations in cities and agglomerations. For instance, population fluctuations in the Prague agglomeration are the subject of work by a group of Czech scientists. Using mobile operators' data, they determined the types of daily rhythms for different parts of the Prague region based on correlation with the location of residential and commercial real estate [34]. They found that mobile operators' data (depending on the time and duration of a person's stay in a particular area) make it possible to distinguish residential, working, transport, and service types of districts in the city. The analysis of daily rhythms provided important information about the actual use of different parts of the city and was implemented for territorial planning.

A group of international scientists [35] investigated longer (seasonal) cycles of human life. They developed population mapping methods to estimate population density using datasets of over 1 billion mobile phone call records from Portugal and France. Scientists found a significant reduction in the summer population in the largest urban agglomerations. In contrast, they noted a significant summer surge in population for seaside, mountainous, and many rural resort areas. Mobile operators' data made it possible to determine winter and summer attractor areas, the degree of their attractiveness, as well as objects that introduce serious deformations into seasonal rhythms.

The study of natural patterns of network interaction of people in space based on "Big Data" provides a possibility of objective identification of the boundaries in settlement structures and leads to the development of new zoning methods. In this regard, it is worth noting the work of British and Belgian researchers on "natural" zoning in their countries using mobile operators' data [36,37]. These studies have shown that, in general, the "telephone" division corresponds well to administrative regions. However, in some cases, unexpected spatial structures are also found.

In addition, it is important to note the possibility of a deeper analysis of mobile operators' data by including additional information about subscribers. Thus, Belgian scientists shed light on some socio-cultural communication differences by including information about the language of communication in the analysis. In addition, American specialists showed the methodology of mobile operators' data using for ethnic and ethno-cultural zoning, as well as for the analysis of ethnic segregation [38].

6.3. Using the Mobile Operators' Data to Study Population Mobility and Build Transport Models

Transport planning and the study of population mobility are one of the most dynamically developing issues in the practical application of mobile operators' data. To analyze transport traffic, mobile operators' data are widely used in Finland, Germany, Spain, Sweden, and some other countries [39,40]. For a long time, mobile operators' data together with GPS navigation have been used in navigation equipment for motorists.

The possibility of obtaining information about the places of residence and work of motorists significantly helps in studying the peak loads on the transport infrastructure. An example of work in this direction is a study by Estonian scientists for Tallinn. The purpose of this study is to identify the main "culprits" of traffic jams during the evening peak hours [41]. The study result was the disproof of the thesis about the leading role of suburban residents in Friday traffic jams. On the contrary, the determining role of citizens leaving the city for recreational and leisure purposes was revealed. An important conclusion of Estonian scientists was the understanding of the reasons for the maximum load on the transport infrastructure on Friday evening. As a result, in the case of Tallinn, it was shown that understanding the transport behavior of certain population groups can help in the analysis and transport planning of settlement systems.

6.4. Using the Mobile Operators' Data to Study Human Behavior and in Urban Studies

Detailed (for example, with the help of special mobile applications) mobile operators' data, as well as their synthesis with other information sources, are widely used in various urban studies and predictive models of socio-economic development of the territory. Thus, statistical models are built by overlaying and comparing data based on mobile phone indicators (average call volumes in a region, call recipients, etc.) with different socio-economic variables (for instance, income level). These models can show patterns and trends in the development of territories.

One work by British specialists [42] is dedicated to the study of the relationship between the level of well-being and the branching of social contacts. It demonstrates that the diversity of individual relationships is closely related to the economic development of local communities. The connection between people's mobility and their social networks is considered in detail in some work of Portuguese scientists [43]. Based on long series of mobile operators' data, the relationship between the strength of social ties and people's movements is shown.

The combination of the theoretical base of the behavioral paradigm and the technological capabilities of cellular communication has contributed to the appearance of studies on human behavior in the urban environment [44]. Models of people's behavior in cities based on mobile operators' data have been developed for many large centers such as New York, Los Angeles, Boston, Harbin, Singapore, London, and Beijing [25,45]. In them, based on the digital tracks of mobile users, the spatial attractiveness of various locations was identified. This helped to better understand the spatio-temporal specifics of the urban space functioning.

A lot of research is devoted to the study of the behavior of different social groups. It is necessary to single out works on the study of mobility in the context of age groups (the cases of Prague and Estonia), ethnic groups (the cases of Estonian and Russian-speaking residents of Tallinn), gender groups (the case of residents of the Tallinn suburbs), and national groups (the case of foreigners in Milan) [46–50]. Behavioral models also include models of the people behavior on long journeys, built on the basis of mobile operators' data in 2007–2017 in Israel, the USA, and the UK [25,51,52].

A promising direction for mobile operators' data use is to study the impact of various events on the settlement system. As part of the "Rome in Real Time" project, scientists studied the population distribution in the city during the celebration of the national team's victory in the final match of the World Cup and Madonna's concert [53].

A group of researchers from the Fraunhofer Institute carried out a similar study in 2008. They investigated the pulsation processes associated with several football matches in Milan [54]. An even larger, but still unrealized, project should have been implemented during the 2012 Olympic Games in London [55]. Another example of a cultural event that has become an object of researchers' attention is the Light Festival in Ghent, Belgium [56].

All of the above projects focused on the study of the spatial structure of places of attraction for people. The case of considering events from a different angle, from the point of view of places of human flows formation, was realized in the work of scientists from the University of Tartu. They measured the "catchment areas" of tourist events using passive positioning data [27,57].

In particular, they confirmed the principle of distance "attenuation" formulated by the Swedish geographer G. Olsson on the basis of V. Tobler's first law, according to which the number of visitors decreases with distance from the event [58,59]. In addition, the researchers identified seasonal patterns, for instance, an increasing proportion of long-distance travelers in the off-season and in winter.

The case of the use of mobile operators' data in the study of political events is the analysis of protest actions within the framework of the so-called "Million March" (Israel, 2011). The new tool helped to accurately describe the social component of the protest. For instance, it turned out that most of the protesters belonged to the poor, and half were residents of Tel Aviv [60]. Thus, mobile operators' data may be of interest not only for studying such events, but also for preventing various kinds of political speculations (for example, regarding frequent disputes about the number of protesters).

6.5. International Projects in Developing Countries

High interest in mobile operators' data is shown by research teams involved in the study of the socio-economic and demographic development of developing countries. In many such countries, especially those that have experienced civil wars, natural disasters, and other humanitarian catastrophes, a population census has not been conducted for forty years or more. As a result, the size, structure, and distribution of the population are very approximate [4]. Moreover, "defective" demographic data also lead to inaccuracies in the calculation of GDP and other economic indicators. This situation is figuratively characterized by scientists as "the statistical catastrophe of Africa" [61]. According to [62], in such countries, Big Data are becoming increasingly important for national statistics, allowing to skip the stage of classical data collection methods and move directly to the era of data collection using mobile phones and satellite imagery.

In addition to eliminating "statistical gaps", mobile operators' data in post-socialist and developing countries are actively used for transport modeling. At the same time, if in the post-socialist countries transport problems are determined by the transformations of settlement structures, accompanied by a change in the directions and volumes of traffic flows, then the main problem of developing countries is rapid urbanization. The cities' growth in them outpaces the infrastructure development, which significantly increases the load on the road network. As a result, roads and public transport systems experience enormous congestion, and people lose a lot of time for work and other transportation. All this, in turn, has negative consequences for economic and social development.

The study [63] showed that it is possible to track citizens' travel routes and use mobile operators' data for more efficient planning and management of transport services. For instance, within the framework of the "Mobility Planning for Africa" project, specialists from the French Orange Labs Institute developed a transport model for Abidjan, the largest city in Côte d'Ivoire, which makes it possible to understand the current and future needs of its infrastructure. With its help, new bus routes have been developed. Travel time by public transport within the city has been reduced by an average of 10%, and some of the research results have been used to plan a possible metro system [63,64].

An example of using mobile operators' data to study poverty is the methodology developed by an international group of scientists for assessing the socio-economic situation in Côte d'Ivoire [65,66].

With the assistance of specialists from Europe and the US, studies of population mobility and transport models' construction were also carried out in India, Morocco, Myanmar, Bangladesh, Sri Lanka, and Senegal. The obtained data on the behavior of large cities' residents in developing countries were simultaneously analyzed and compared with the available information for developed countries. This gave very interesting results. For instance, the average distance traveled by city dwellers in developing countries is six times less than in the developed world. However, urban dwellers in developing countries travel longer distances in their daily lives compared to suburban dwellers, which is not the case for European or American metropolitans [67].

The unique capabilities of mobile operators' data in "situational" analysis determine the high potential for their use in monitoring the consequences of various types of emergencies and for studying "shock pulsations" of the population, especially common in developing countries. Mobile operators' data obtained in "real time" with their operational processing and use can be a valuable source of information for emergency services in situations where timely information on the movements and location of affected people is required, for instance, in the event of natural or man-made disasters, armed conflicts, or epidemics [35].

During the earthquake in the Republic of Haiti in 2011, population displacement estimates made using data from the country's largest mobile operator, Digicel, agreed with a high degree of accuracy with the results of a large retrospective population survey conducted by the United Nations [68]. This demonstrated the applicability and high usefulness of this data source for operational monitoring of the situation during and after a natural disaster. As the case of Haiti has shown, information about the movements of people after a disaster can help organize the provision of food, water, and medicines to the victims.

A team of scientists from Russia is working on assessing the vulnerability of the population to natural and man-made hazards in the case of Moscow urban districts. In studies [13,69,70], researchers presented their methodology based on mobile operators' data, allowing to identify areas of Moscow characterized by the maximum vulnerability of present population. The authors evaluated the internal differentiation of urban space in terms of the degree of technogenic risk based on data on the probability of people staying in the areas of potentially hazardous enterprises in various time cycles (daily, weekly, seasonal). An interesting conclusion was the quantitative assessment of the discrepancy between official statistics and documents and the actual situation.

In cases of natural disasters associated with the spread of infectious diseases, mobile operators' data can be used to assess the risks of the geographical spread of the disease, disease importation routes, and determine the parameters of the quarantine zone. Among the studies devoted to the spread of diseases, it is worth noting the work of specialists from the Karolinska Institute of Sweden (the case of malaria in Kenya) as well as a study by an international scientist team on modeling the diffusion of epidemics [71,72]. By tracking the scale of migration from the epidemic epicenter to other areas, Swedish scientists have built graphs of disease import routes that spatially characterize the epidemiological picture of the malaria spreading.

7. Conclusions

As international practice shows, information provided by a mobile operators' data is a promising and representative analytical tool that can help improve the quality of results in many research areas. These data can act both as an independent information resource and in combination with traditional statistical resources or other types of Big Data.

World research experience demonstrates how the analysis of daily data provided by mobile operators can complement the results of a traditional census. Information about the location of subscribers gives benefits in terms of measuring the dynamics and distribution of people. In addition, the combination of mobile operators' data with information from traditional statistics, as well as other sources of Big Data, such as remote sensing, improves the spatial and temporal resolution of geoinformation in the study of various demographic and socio-economic processes.

Mobile operators' data make it possible to estimate the size, density, and distribution of the population with high spatial and temporal detail and, if necessary, regardless of the administrative-territorial division. Their use allows identifying the transformations in population distribution depending on the time of day, days of the week, season of the year, or a specific event. Based on demographic statistics, historical analysis, real-time monitoring, mobile operators' data can be used to build demographic and migration forecasts, in risks models, etc.

An analysis of people's movements in the "home–work–leisure–recreation" system allows for more detailed study of the settlement systems, zoning, and construction of transport and behavioral models. An important application is the possibility of incorporating the obtained results in statistics and territorial planning.

At the same time, the possibilities of using new data sources are not limited to their introduction into the existing system of statistical indicators. They can be used to create new indicators or to improve and calibrate existing ones. These useful new indicators include daily or seasonal population values, pendulum labor migrations, the elasticity of settlement system, etc. Diversity and high penetration rate of mobile telephony leads to a better understanding of human behavior in time and space. Used in conjunction with traditional surveys, these data can provide an opportunity to reduce sample sizes, lead to cost savings, and reduce respondent burden in sociological surveys.

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