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RESEARCH ARTICLE

Effects of Demand Estimates on Evaluation and Optimality of Service Centre Locations

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Public service systems, such as emergency health-care, police or fire brigades are critical for day-to-day functioning of the society. To design and operate these systems efficiently a lot of data needs to be collected and properly utilised. Here, we use the OpenStreetMap data to model the demand points, which approximate the geographical location of customers, and the road network, which is used to access or to distribute services. We consider all inhabitants as customers, and therefore to estimate the demand, we use the available population grids. People are changing their location in the course of the day and thus the demand for services is changing accordingly. In this paper, we investigate how the used demand estimate affects the optimal design of a public service system. We calculate and compare efficient designs corresponding to two demand models, a night time demand model when the majority of inhabitants rests at home and the demand model derived from the 24-hours average of the population density. We propose a simple measure to quantify the differences between population grids and we estimate how the size of differences affects the optimal structure of a public service system. Our analyses reveal that the efficiency of the service system is not only depended on the placement strategy, but inappropriate demand model has significant effects when designing a system as well as when evaluating its efficiency.

Keywords: public service systems, population grids, spatial planning and policy

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1. Introduction

Public service systems provide a broad range of critical services to the general public. Real-world examples of such systems are networks of hospitals, schools, ambulances, fire or police stations. In this paper, we evaluate the impact of spatiotemporal variations in the demand for services on the efficient spatial design of the public service systems. Models of the demand are relevant either when designing a service system from scratch or when evaluating properties of an existing system. The service system design problem consists of finding a suitable set of service centre locations from where the services could be efficiently distributed to customers. When evaluating the properties of an existing service system, spatial positions of service centres are known, and the goal is to evaluate how well the spatial design corresponds to the demand generated by customers.

Basic data requirements are shared across various types of public service systems. They consist of the suitable set of demand points representing geographical positions of customers, the road network infrastructure used to distribute services or access the service centres, and the population density data of suitable resolution to estimate the demand for services. These requirements are identical for the design of a new system and also for the evaluation of an existing system.

Combining the OpenStreetMap data with two types of population grids, we build a data model, which is later used to compute the optimal design of a hypothetical public service system. To the best of our knowledge, this is the first attempt to quantify the effects of spatio-temporal variations in the demand on the efficient placement of service centres. Using large set of efficient service center locations, we vary the spatio-temporal model of demand and we quantify the effects on the estimated system efficiency. We compare the size of both types of effects. Our results show that the type of the population grid used to model the demand for services should be carefully selected. The misplacement of the population grid may have a significant impact on the efficiency of the resulting service system, a remark of caution to system designers.

The paper is organised as follows: section 2 provides a structured review of the literature. In section 3, we describe the data, preparation procedures and their justifications. Results of numerical experiments are reported in section 4. To conclude, we summarise our main findings in section 5.

2. Background

The number of existing location problems that can be used to find the optimal spatial design of a service system is overwhelming (Eiselt and Marianov 2011, Daskin. M. 1995, Drezner 1995). The p-median problem is one of the most frequently studied and used location problems (Hakimi 1965, Calvo and Marks 1973, Berlin G N *et al.* 1976, Janáček *et al.* 2012). The goal is to locate exactly p service centres in a way, that the sum of weighted travel times from all customers to service centres is minimised. The problem is NP-hard (Kariv and Hakimi 1979). For a comprehensive overview of applications and solving methods see references Marianov and Serra (2002, 2011). Exact solving methods are summarised by Reese (2006) and heuristic methods by Mladenović *et al.* (2007).

To describe the p-median problem, we adopt the well-known integer formulation proposed by ReVelle and Swain (1970). We consider all n demand points (DPs) as possible candidate locations. The travel time on the fastest path between demand points i and j is denoted as t_{ij}. We associate to each demand point a weight w_i that is representing the number of customers assigned to the demand point i. Decisions are described by the set of binary variables:

$$x_{ij} = \begin{cases} 1, & \text{if demand point } i \text{ is assigned to service centre } j \\ 0, & \text{otherwise,} \end{cases}$$

$$y_j = \begin{cases} 1, & \text{if a service centre at the candidate location } j \text{ is open,} \\ 0, & \text{otherwise.} \end{cases}$$

The p-median problem can be formulated as follows:

$$\text{Minimise} \qquad f = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i t_{ij} x_{ij} \tag{1}$$

subject to

$$\sum_{j=1}^{n} x_{ij} = 1 \qquad \text{for all } i = 1, 2, \ldots, n \tag{2}$$

$$x_{ij} \leq y_j \qquad \text{for all } i, j = 1, 2, \ldots, n \tag{3}$$

$$\sum_{j=1}^{n} y_j = p \tag{4}$$

$$x_{ij}, y_j \in \{0, 1\} \qquad \text{for all } i, j = 1, 2, \ldots, n. \tag{5}$$

The objective function (1) minimises the sum of weighted travel times from all customers to service centres. The constraints (2) ensure that each customer is allocated to exactly one service centre. The constraints (3) allow to allocate customers only to located service centres, and the constraint (4) makes sure that exactly p service centres are located.

2.1. *Datasets*

Service systems typically cover large geographical areas, and the system design or system quality evaluation are data-intensive activities. Customers are modelled by the set of demand points representing their spatial distribution (Francis *et al.* 2009). Typically, this set can be derived from the specification of the real-world problem or we can approximate DPs from the knowledge of the land use/land cover (LULC). Travel distances or travel times can be deduced from the road network. Considering different classes of roads helps to determine the average travel speed more precisely. Typically, when modelling service systems in urban or rural areas the number of DPs is extremely vast, since each private residence might be a DP. Often it is impossible, and also unnecessary, to include all DPs to the model. The solution is to use an aggregation. There is a strong stream of literature studying aggregation methods and corresponding errors (for comprehensive overview see Francis *et al.* 2009, and references therein). Various sources of aggregation errors are discussed by Hillsman and Rhoda (1978), Erkut and Bozkaya (1999) and Hodgson *et al.*

1997. Many service systems are supposed to serve the general public, i.e. all citizens are considered to be customers and the demand for services is assumed to be proportional to the population. Here, we also take this assumption. However, it should be noted that in cases when only a specific part of the population is served by the system (e.g. children of a certain age), it might be misleading to derive the demand from the general population data. The size of the surrogation error caused by the wrong estimation of the population could be roughly five times as high as aggregation error (Hodgson and Hewko 2003).

In this paper, we consider volunteered geographic information (VGI) as a source of data that can be used to extract streets and road infrastructure. Moreover, it provides other useful information such as positions of buildings, residential areas, industrial areas and commercial areas, which can be used to define DPs. VGI is created by volunteers, who produce data through Web 2.0 applications and combine it with the publicly available data (Goodchild 2007). VGI has been criticised due to potential data quality issues (Flanagin and Metzger 2008, Jackson *et al.* 2013), and researchers are looking for mechanisms how to ensure the data quality (Bishr and Mantelas 2008), how to protect against deliberate data damages (Neis *et al.* 2012) or how to mitigate the effect of completeness errors in VGI data by machine learning approaches (Hagenauer and Helbich 2012).

One of the most successful examples of VGI is the OpenStreetMap (OSM) project. OSM gives the opportunity to download spatial data without any costs or fees and enables the use of data for individual projects (Zielstra and Zipf 2010). OSM data has already been used in various applications, such as automatic derivation of three-dimensional CityGML models (Goetz and Zipf 2012), mapping land-use patterns (Jokar Arsanjani *et al.* 2013), design of a recommendation system providing tourists with the most popular landmarks as well as the best travel routings between the landmarks (Sun *et al.* 2013) and population mapping at the building level (Bakillah *et al.* 2014).

To estimate the demand for services, the population density data are needed. The best way to produce a gridded map of a population density is to count the number of people in each cell of the grid (bottom-up approach). Nevertheless, not all of the European countries are releasing bottom-up population grids, and only a few of them provide the resolution finer than 1km. Often, the distribution of grids is limited by confidentiality rules (Gallego 2010). An alternative is to reallocate data from available census zones (communes, wards) into regular grid cells using disaggregation methods (top-down approach) (Zandbergen 2011). Spatial disaggregation is a variant of long studied areal interpolation problem of estimating values for a set of target zones based on values recorded for another set of incongruent source zones (Goodchild and Lam 1980, Tobler 1979). Simple methods estimate the target values based on assumptions such as homogeneous spatial distribution (in areal weighting) or distance decay (Bracken and Martin 1989) without the use of additional spatial information. Intelligent (or dasymetric) methods employ ancillary spatial data related to the disaggregated variable to improve the estimates. Martin *et al.* (2000) note that the accuracy of the resulting map is influenced more by quality and appropriateness of the used ancillary data than by the particular disaggregation algorithm. The most frequently used ancillary data in population disaggregation are LULC categorical maps, typically derived from classification of satellite/aerial imagery (Langford and Unwin 1994, Fisher and Langford 1996, Eicher and Brewer 2001, Mennis 2003, Holt *et al.* 2004, Gallego 2010). Other types of ancillary data have been proposed such as road networks (Xie 1995, Reibel and Bufalino 2005), satellite images (Harvey 2002, Li and Weng 2005) and cadastral data (Tapp 2010). Multiple types of ancillary datasets can be combined to increase the accuracy (Dobson *et al.*

2000, Bhaduri *et al.* 2002, Batista e Silva *et al.* 2013).

Some disaggregated population models are based on source data from censuses, recording people at their permanent residences (approximately a night-time distribution of the population). The actual distribution of population changes dynamically following a complex movement pattern. The most common type of movement is daily commuting to workplaces and schools. Models of day-time population reflect the distribution of people in commuting destinations. In some locations extreme differences between the two distributions occur (e.g. for city business districts, industrial zones or shopping malls). Another type of spatio-temporal conceptualisation of population density is ambient population (Dobson *et al.* 2000, Sutton *et al.* 2003), modelling an average occurrence of people over a certain period of time (e.g. one day or a year). In such a model certain non-zero densities should be attributed to spaces like highways, parks or agricultural land. Ambient models may be preferable, if no specific time of the day is characteristic for the studied problem.

3. Methods

In this paper, we compare public service systems designed based on residential and ambient demand models. The demand models are derived from a residential population grid produced by Batista e Silva *et al.* (2013) (RP hereinafter) and LandScan ambient population grid (Dobson *et al.* 2000, Bhaduri *et al.* 2002) (AP hereinafter). Choice of Landscan was straightforward as it is the only one well-recognised ambient population model covering Slovakia. The AP grid is available on the resolution of 30 seconds of arc (approximately 1 km), defined in the geographic coordinate system. We employed the 2012 version. The source population data for this data set comes from a national census that took place in 2011. As candidate data sets for residential population grid, we considered three population grids: Global Rural-Urban Mapping Project (Balk *et al.* 2006), residential grid that is provided by the Austrian Institute of Technology (Steinnocher *et al.* 2011) and residential population grid RP by Batista e Silva *et al.* (2013). Residential grid RP was chosen with respect to the best coincidence in spatial resolution, coordinate system and reference year with the AP grid. The population grid by Batista e Silva *et al.* (2013) is based on ETRS89-LAEA, the cell size is only 100 m. Thus, it can be projected to the LandScan cells relatively reliably. The disaggregation was based on 2006 commune population counts and CORINE Land Cover map enhanced by Soil Sealing, Urban Atlas, Tele Atlas and other data were used as ancillary data.

In the next subsection, we analyse the RP and AP grids by comparing the differences between them. Daily travel times are relatively short for the majority of the population (Bazzani *et al.* 2010, Kölbl and Helbing 2003). Thus, by reducing the resolution of population grids, the differences between AP and RP grids should diminish. Population grids are coming from very diverse sources. RP grid was produced in Europe and made public by Batista e Silva *et al.* (2013). Landcan 2012 was made in U.S. and we purchased it directly from East View publisher. The aim of these analyses is to use this expected property of population grids to validate their quality and compatibility.

3.1. *Comparison of Residential and Ambient Population Grids*

We evaluate the differences between RP and AP grids for the geographical area of the Slovak Republic considering various scales of the spatial resolution. Grids cannot be compared directly. Therefore, to minimise the bias, arising from different spatial resolutions of both grids, we projected RP cells onto AP cells by recalculating the population proportionally to the area of cell intersections and we resampled the RP grid to the spatial resolution of 1 km. For each grid cell $k = 1, 2, \ldots, s$ in the population grid $l \in \{AP, RP\}$, where s is the number of grid cells, we denote as c_k^l the population of the cell k. To evaluate which population grid assigns larger population to individual cells, we compute the difference:

$$\delta_k = c_k^{RP} - c_k^{AP}. \tag{6}$$

Values δ_k are shown in Figure 1(a-b) for two selected areas: Bratislava (the capital of the Slovak Republic) and Košice (the second largest Slovak city). The general pattern revealed by this comparison confirms that AP allocates larger population to industrial and commercial areas and smaller population to residential areas. Values δ_k form an image of absolute differences between population grids and thus they do not allow to spot relative differences, which might be small in terms of absolute values. Therefore, we define the relative difference as:

$$\phi_k = \frac{\delta_k}{\frac{1}{2}(c_k^{RP} + c_k^{AP})}. \tag{7}$$

It is not obvious which value, c_k^{RP} or c_k^{AP}, would be more suitable as a normalisation factor and thus we normalised δ_k by the average value. Figure 1(e) shows ϕ_k values for the entire area of the Slovak Republic. The AP grid attributes some population to non-urban areas, where the RP is zero (blue areas in the Figure 1(e). Although, population density attributed by the AP grid to non-urban areas is low, these areas are geographically large. Thus, they could significantly influence the travel times from service centres to customers.

To check whether RP and AP grids are still comparable, when reducing the spatial resolution, we changed the spatial resolution to 2 km, 4 km, 8 km and 16 km. For the area of the Slovak Republic, we evaluated the similarity of population grids by calculating the Pearson product-moment correlation coefficient r between population values attributed to individual grid cells. We obtained the following sequence of values: $r_{1\text{ km}\times 1\text{ km}} = 0.721$, $r_{2\text{ km}\times 2\text{ km}} = 0.853$, $r_{4\text{ km}\times 4\text{ km}} = 0.919$, $r_{8\text{ km}\times 8\text{ km}} = 0.949$ and $r_{16\text{ km}\times 16\text{ km}} = 0.978$. Figures 1(f-g) show scatter plots for the spatial resolutions of 1 km $\times$ 1 km and 16 km $\times$ 16 km, respectively (for all scatter plots see Figure 2 of the supplementary information file). Total difference between population grids clearly decreases (correlation increases) when decreasing the resolution. That is in agreement with our expectations and it validates, at least partially, the correctness of the used population grids.

In summary, we find large absolute differences between population grids in urban areas, and small differences in non-urban areas, which, however constitute large geographical areas. The cross-scale analysis reveals that if the resolution is high, differences between population grids are non-negligible. When lowering the resolution, differences are quickly getting small. Thus, these analyses indicate that differences between population grids can have an impact on the efficient spatial design of service systems, when the area served from one service centre is small.

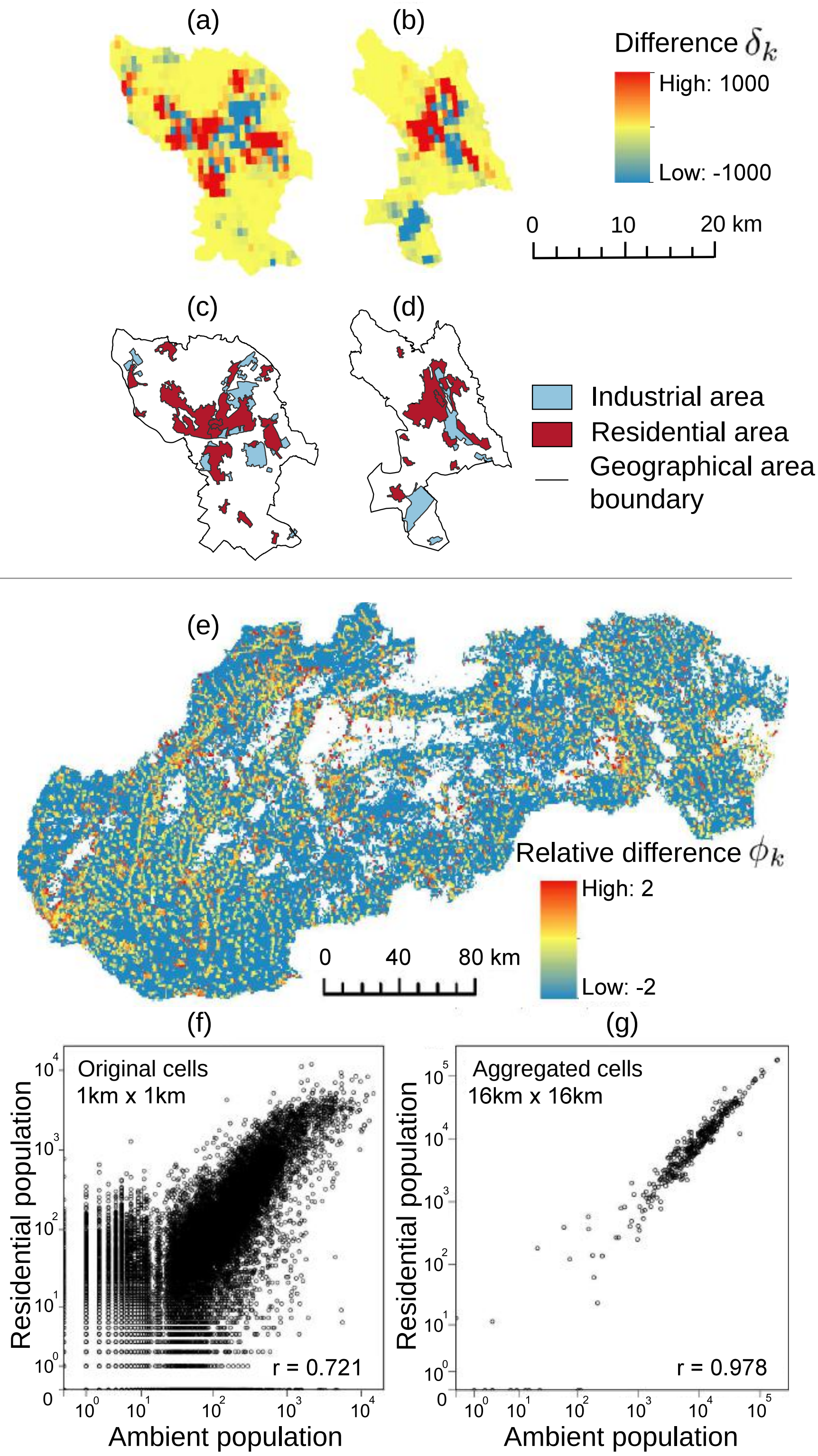

Figure 1. Evaluation of differences between AP and RP grids. (a)-(b) Colour maps showing absolute differences for two selected geographical areas: (a) Bratislava (the capital of the Slovak Republic) and (b) Košice (the second largest Slovak city). (c)-(d) Residential and industrial areas (source: CORINE Land Cover 2006) (c) Bratislava (d) Košice. (e) Colour map of relative differences. (f) Scatter plot of the cell population comparing the AP and RP grids for the resolution of 1 km × 1 km. (g) Scatter plot of the cell population comparing the AP and RP grids for the resolution of 16 km × 16 km.

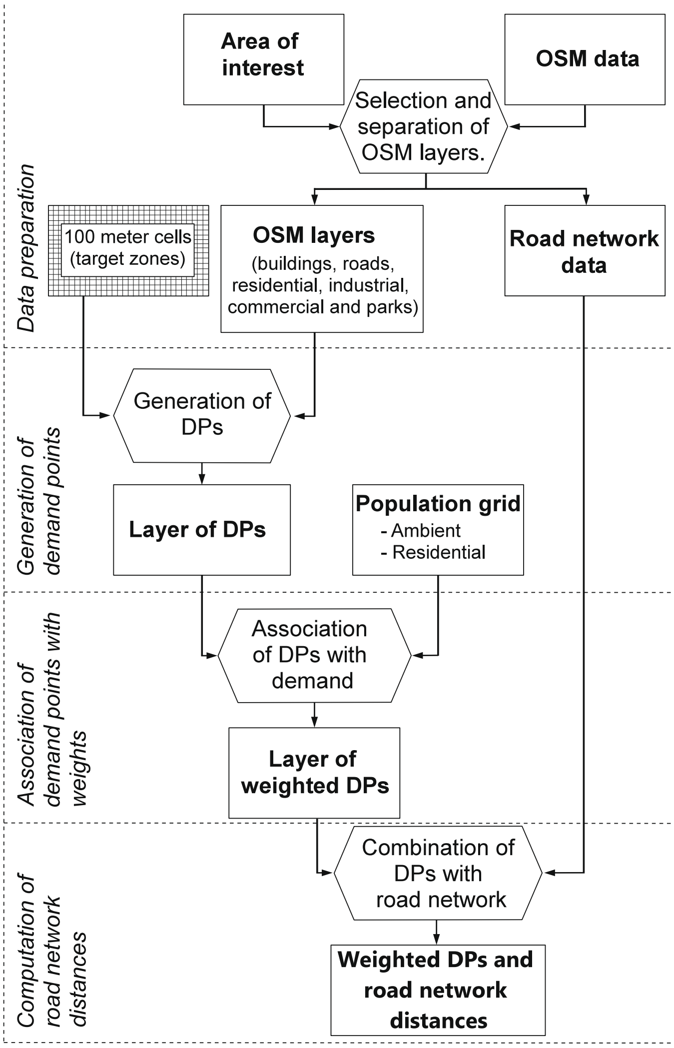

Figure 2. Work-flow of input data processing for the service system design problem from OSM data and population grids.

3.2. *Data Model*

In this subsection, we briefly describe the procedure used to prepare the input data for the service system design problem. This procedure consists of four steps that are illustrated in Figure 2. Steps have to be executed in this order: data preparation, generation of demand points, association of weights with the demand points and computation of road network travel times between all pairs of demand points.

3.2.1. Data Preparation

In the first step, data are extracted from the OSM database. Geographical features that are suitable to define the position of DPs depend on the application. Here, our goal is to capture the position of inhabitants independently on the time of the day. Therefore, we selected five basic OSM layers that allow to estimate the positions of inhabitants when they are at home, at work and also when they are travelling. Thus, to model demand points, we consider data layers describing positions of buildings, roads, residential, industrial and commercial areas. The layer of roads is later used to calculate the travel times between demand points.

3.2.2. Generation of Demand Points

Demand points are generated in two steps: In the first step, we create a spatial grid, which consists of uniform square cells. The size of cells has a twofold effect. On one hand side, it affects the precision in assigning population to DPs. Unified resolution of population grids is 1×1 km. On the other hand, resolution of cells affects the precision in estimating the travel times between DPs. Our primary goal is to evaluate the effect of using different types of population grids. Hence, to make sure that the precision in measuring travel times is higher than in the demand estimate, we use the resolution that is one order of magnitude higher than the resolution of available population grids. Thus, to generate DPs, we decided for the size of square cells 100×100 metres. We intersect each cell with all OSM data layers described in the previous subsection. We search for intersections between cells of the spatial grid and points, polylines and polygons that constitute selected OSM layers. In the second step, a demand point is situated as a centroid of each cell with a non-empty intersection with an OSM data layer.

3.2.3. Association of Demand Points with Weights

In the previous step, we obtained a set of demand points that are described by their coordinates. Next, we assign a weight representing number of customers to each demand point. To make both population grids comparable, we scaled the resolution of the residential population grid from 100 m $\times$ 100 m down to the resolution of 1 km $\times$ 1 km. First, we calculate spatial geographical areas associated with demand points using Voronoi diagrams. Second, we assign weights to demand points by intersecting Voronoi polygons with the population grid. The population assigned to a demand point is proportional to the population and to the area of the population grid cells intersecting the Voronoi polygon.

3.2.4. Computation of Road Network Travel Times

In the last step, all demand points are connected to the closest road segment. To minimise the length of the connection between the demand point and the road network, when it is necessary, we split the closest polyline describing the road segment by adding an intermediate node. From all road segments and demand points, we compiled the directed graph $G(V, E, t)$, with node-set V, edge-set E and edge-travel time function t: $E \to \mathrm{R}_0^+$. Travel time is estimated from road classes considering the speed limits [1]: 50 km/h for roads classified as residential, service and unclassified; 90 km/h for the primary, secondary and tertiary roads and 130 km/h for motorways and trunk roads. We measure the travel time between demand points in seconds. The quality and completeness of the OSM road network is discussed in the section 1 of the supplementary information file. For the study area of the Slovak Republic, we obtained the graph with 1 966 092 nodes (including 666 824 demand points) and 1 884 537 edges.

4. Results

To find the optimal location of service centres for the p-median problem, we use the state-of-the-art algorithm ZEBRA (García *et al.* 2011). GIS software offer tools for locating-allocating service centres, however, they are typically based on heuristic algorithms providing suboptimal solutions. We decided to use exact algorithm ZEBRA, to rule out from

[1] `http://ec.europa.eu/transport/road_safety/going_abroad/slovakia/speed_limits_en.htm`

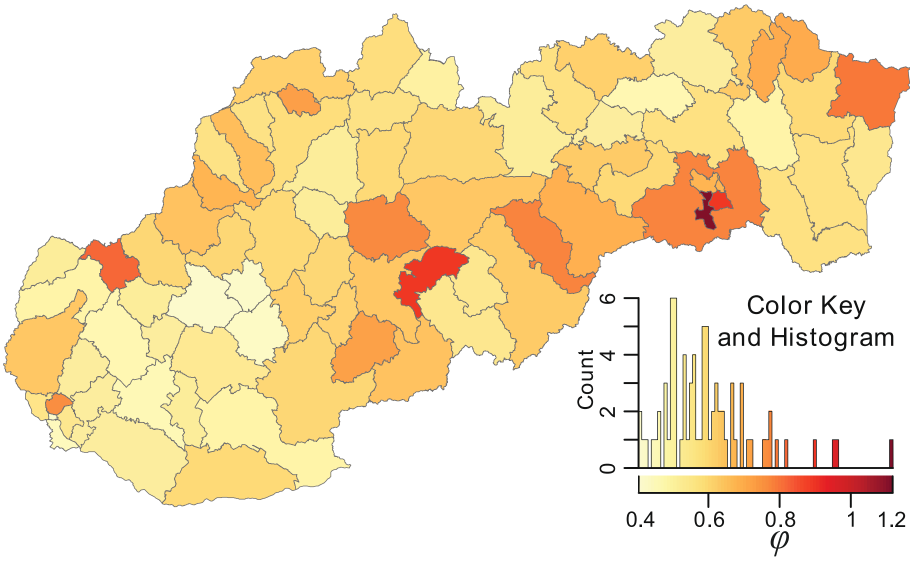

Figure 3. Choropleth map and histogram of φ values for all 79 administrative districts of the Slovak Republic. Values φ are color-coded according to the color key that is shown below the histogram.

evaluations the errors that could be caused by suboptimal solutions. To be able to solve as large instances as possible, we compiled 64 - bit version of the ZEBRA algorithm, and we run computations on the high-performance cluster, while setting the memory limit to 90 GB and the time limit to seven days. Our goal is to gain better understanding of the relation between the level of differences in the demand resulting from using AP and RP population grids and the size of the impact on the optimal location of service centres. In order to do so, we need a simple measure, which can be used to quantify the differences between the demand models. For this purpose, we adapt the measure RTAE, defined in the reference Batista e Silva *et al.* (2013). For each DP $t = 1, 2, \ldots, n$, where n is the number of DPs, we denote as g_t^l the population projected from the population grid $l \in \{AP, RP\}$ to the DP t. Similarly as in Eq.(7), we normalise the total absolute deviation by the average population attributed to individual demand points:

$$\varphi = \frac{\sum_{k=1}^{n} |g_k^{RP} - g_k^{AP}|}{\frac{1}{2}\sum_{k=1}^{n}(g_k^{RP} + g_k^{AP})}. \tag{8}$$

We start by computing values of φ for all 79 districts of the Slovak Republic. The choropleth map and histogram of φ values are shown in Figure 3. The minimum value $\varphi = 0.416$, we found for the district of Partizánske and the maximum value $\varphi = 1.118$ was obtained for the district of Košice II. The histogram of φ values shows, that the large majority of values does not exceed value 0.8. To study the dependence of the relative errors on the parameter φ, we selected a sample of ten districts (see Table 1), to cover the entire range of φ values uniformly. The sample covers 9.64 % of the population of Slovakia. Nowadays, 113 professional fire stations, 273 emergency ambulance stations, 405 police stations (239 out of them were established by the state government and 166 were established by the self-governed municipalities) and 1 500 post offices operate in the Slovak Republic. The entire population that is served by these systems consists of

Table 1. Basic information about geographical areas selected based on the value φ.

District	φ	**Number of DPs**	**Size** $[km^2]$	**Population** (AP/RP)
Partizánske	0.416	4 873	301	48 165 / 47 553
Hlohovec	0.502	5 525	267.2	46 836/ 45 519
Ružomberok	0.589	5 791	646.8	59 915/ 59 225
Ilava	0.690	5 449	359	63 031/ 61 168
Revúca	0.778	6 397	730.2	42 283/ 40 761
Snina	0.820	5 510	804.7	39 609/ 39 157
Myjava	0.901	5 638	327	28 574/ 27 884
Detva	0.950	7 966	449.2	35 346/ 33 568
Košice IV	0.966	2 791	60.9	80 461/ 58 180
Košice II	1.118	3 537	80.5	77 989/ 78 793

5 415 949 inhabitants. Taking into account the real number of service centres, we calculated the average number of citizens that are served from one centre. For the areas that constitute our benchmarks, we estimated the corresponding number of service centres using the information about the population. Based on these numbers, we roughly estimated the realistic range for p values as $1, \ldots, 40$.

Let us denote the optimal location vector obtained by solving the p-median problem (1)-(5) when using the weights w^k, derived from the population grid $k \in \{AP, RP\}$, as $(y_1^k, y_2^k, \ldots, y_n^k)$. Value of the objective function (1) that is associated with the solution $(y_1^k, y_2^k, \ldots, y_n^k)$ for $k \in \{AP, RP\}$ and with the weights w^l, derived from the population grid $l \in \{AP, RP\}$, can be calculated as:

$$f^{k,l} = \sum_{j=1}^{n} \min\{(t_{ij} w_j^l) : i \in \{1, \ldots, n\}; y_i^k = 1\}. \tag{9}$$

Thus, the objective function value $f^{k,l}$ represents the total sum of minimum travel times between the optimal positions of service centres and positions of individual citizens. Locations of service centres are optimised with respect to the geographical positions of individual citizens derived from the population grid k. Located service centres are evaluated with respect to positions of individual citizens derived from the population grid l.

To evaluate the error caused by the interchange of population grids, we adopted two standard error measures used in the location analysis Francis *et al.* (2009). The absolute error is the difference between the objective function values corresponding to two distinct situations. In the first situation, population grids k and l are different. Grid k is used in the case when we search for the optimal location of service centres. Grid l is used in the case when we calculate the value of objective function corresponding to the optimal solution. In the second situation, we use in both cases the same population grids. Thus, the absolute error is defined as:

$$\Delta_m^{k,l} = f^{k,l} - f^{m,m}, \tag{10}$$

where $k, l, m \in \{AP, RP\}$ and $k \neq l$. Objective function values are strongly dependent on the value p. While increasing p, the objective function value is decreasing. Therefore, values of the absolute error are not comparable across different p values. For this reason, we evaluate the relative error Francis *et al.* (2009), Erkut and Bozkaya (1999), Hodgson and Hewko (2003):

$$\Phi_m^{k,l} = \frac{\Delta_m^{k,l}}{f^{m,m}}, \tag{11}$$

where $k, l, m \in \{AP, RP\}$ and $k \neq l$. Values $\Delta_m^{k,l}$ and $\Phi_m^{k,l}$ close to zero indicate that population grids can be interchanged without any significant errors.

In the analyses, we calculate the absolute and relative *location* errors $\Delta_l^{k,l}$ and $\Phi_l^{k,l}$, where $m = l$ and the absolute and relative *evaluation* errors $\Delta_k^{k,l}$ and $\Phi_k^{k,l}$, where $m = k$ for $k, l \in \{AP, RP\}$ and $k \neq l$. The location errors $\Delta_l^{k,l}$ and $\Phi_l^{k,l}$ quantify the difference between values of the objective function, for two optimally located sets of service centres —first computed on the population grid k and second computed on the population grid l— while the objective function values are calculated using the population grid l. Hence, they measure the effect of interchanging the population grids when determining the optimal positions of service centres. The evaluation errors $\Delta_k^{k,l}$ and $\Phi_k^{k,l}$ represent the difference between two values of the objective function that correspond to one location of service centres. But when calculating objective function values, we use two different sets of weights derived from the population grids k and l, respectively. Thus, evaluation errors quantify the effect of interchanging population grids, when evaluating the objective function value for a given location of centres.

Values $\Delta_l^{k,l}$, $\Delta_k^{k,l}$, $\Phi_l^{k,l}$ and $\Phi_k^{k,l}$ obtained for selected geographical areas and selected p values $3, 5$, and 10 are shown in Figures 4 and 5. For the complete results, covering the realistic range of p values, please refer to Figures 4 and 5 of the supplementary information. We note that we found very similar results, when instead of travel times, we use the shortest distances in the objective function. As the travel times are more relevant when dealing with the service systems, we present only them.

For small values of φ, where both grids are similar, location errors are small. As the value φ is growing, the location error grows as well. In extreme cases, such as the district of Košice II where $\varphi = 1.118$, we observe exceedingly large location and evaluation errors. The area of the district Košice II includes large steel producing industrial area in the south and the densely inhabited areas on the north. Thus, many people travel from the north to the south in the morning and back in the evening. During the night, the industrial area is almost empty. In this case, the population patterns are significantly different when interchanging the population grids. Consequently, different population patterns result in considerable differences in optimal service centre locations (for illustration see Figures 6 and 8 of the supplementary information). On the contrary, for small φ values, for

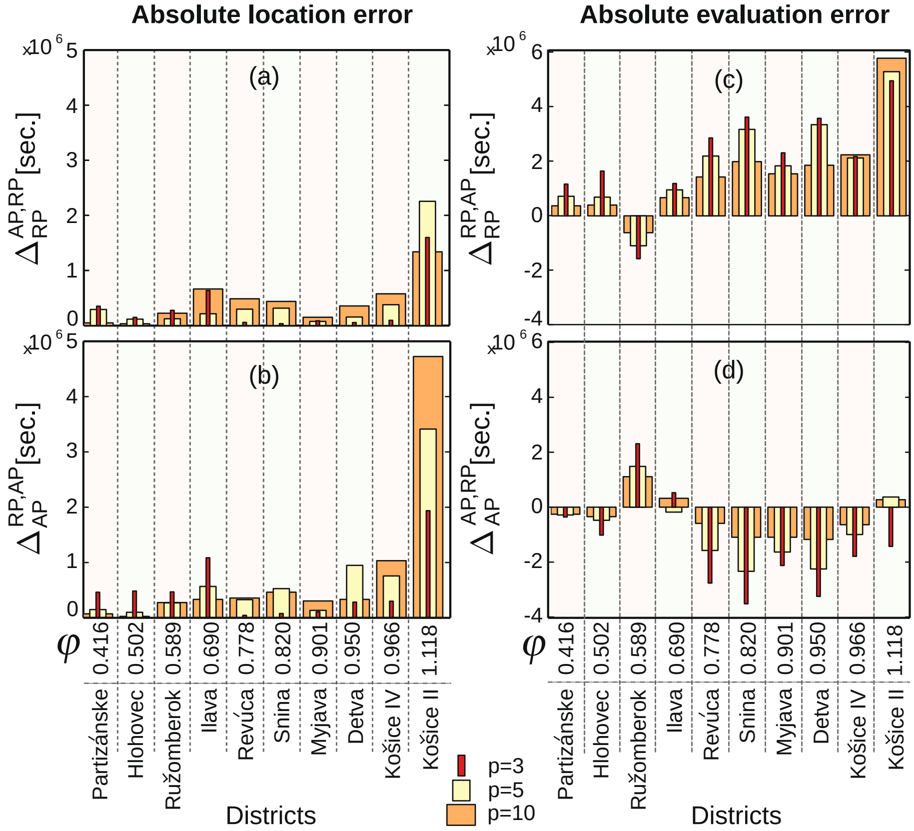

Figure 4. (a),(b) The absolute location error $\Delta_l^{k,l}$ for selected values of $p = 3, 5, 10$. (c),(d) The absolute evaluation error $\Delta_k^{k,l}$ for selected values of $p = 3, 5, 10$. Districts are ordered from left to right according to the ascending φ values. More details about the districts are listed in Table 1.

example in the district of Partizánske where $\varphi = 0.416$, the population differences are only modest. Here, we also find the optimal location of service centres forming similar spatial patterns (for illustration see Figures 7 and 9 of the supplementary information).

When value φ is equal or larger than 0.82, we systematically find significantly larger objective function values when we use AP grid to evaluate the travel times than what we find for RP grid. That is because the AP population has a tendency to be more outstretched in space. It has direct consequences for errors. Location errors grow when φ is increasing. Relative evaluation errors $\Phi_k^{k,l}$ (similarly also absolute evaluation errors $\Delta_k^{k,l}$) behave differently. When computing evaluation error, one layout of located service centres is evaluated using two different population grids. If φ is large enough, for AP we find significantly larger objective function values than for RP, independently on the located service centres. That explains why evaluation errors $\Delta_{RP}^{RP,AP}$ and $\Phi_{RP}^{RP,AP}$ are larger than corresponding location errors and why evaluation errors $\Delta_{AP}^{AP,RP}$ and $\Phi_{AP}^{AP,RP}$ are non-monotonic. Thus, the difference between population layouts tends to have a stronger impact when evaluating the objective value than the use of different optimal layouts of service centres.

(Hillsman and Rhoda 1978) warned that location error caused by uncertainty in input data larger than 2% (for large service areas) and 8% (for small service areas) could be large enough to potentially affect the methodological and substantive interpretations of the results of research on spatial systems. When evaluating the difference in the objective function caused by the exchange of population grids, we found that the errors often

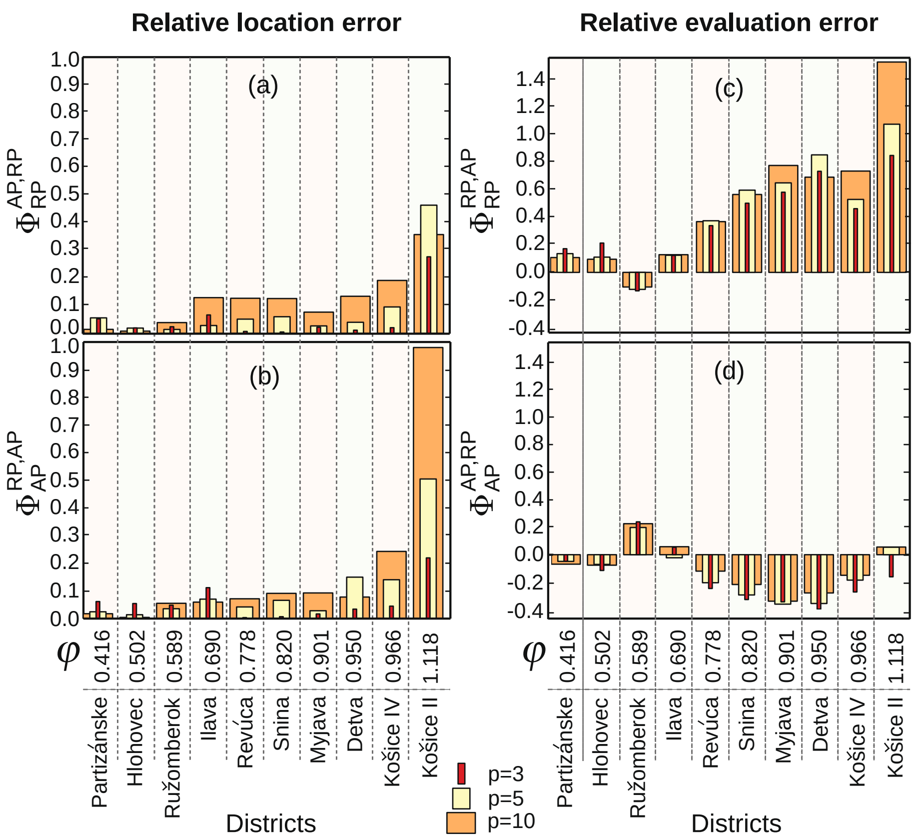

Figure 5. (a),(b) The relative location error $\Phi_l^{k,l}$ for selected values of $p = 3, 5, 10$. (c),(d) The relative evaluation error $\Phi_k^{k,l}$ for selected values of $p = 3, 5, 10$. Districts are ordered from left to right according to the ascending φ values. More details about the districts are listed in Table 1.

exceed these values. Moreover, in some cases, when the difference between population grids measured by φ is large, the errors are significantly larger. These findings give clear evidence that the proper choice of the population grid plays an important role when designing the optimal structure of public service systems. Moreover, the quantity φ seems to be a relevant indicator, which can be able to estimate the role of differences between population grids on the location error, when searching for an optimal location of service centres. Our results cannot be fully generalised to other areas than the Slovak Republic, but we assume that the effects of differences between AP and RP grids, measured by the parameter φ, could lead to similar errors also elsewhere.

For some applications of service systems, we consider the warnings introduced by (Hillsman and Rhoda 1978) as overstated. How relevant is a given value of location or evaluation errors cannot be easily generalised. Each service system involves many uncertainties, which arise from hardly predictable situations. For example, the travel times that we used as a measure to validate the efficiency of a service system, may in some areas vary due to traffic conditions by more than 20% Jenelius and Koutsopoulos (2013). Thus, in such a case, location error smaller than 20% may not be of high importance. Thus, it is up to the designer to estimate the present level of uncertainties considering the local conditions and type of the service system.

In Figure 6, we extracted from results, the maximal, the average and the minimal $\Phi_k^{k,l}$ and $\Phi_l^{k,l}$ values to roughly estimate the potential errors that could be caused by the interchange of two population grids as a function of the parameter φ. Figure 6 can be

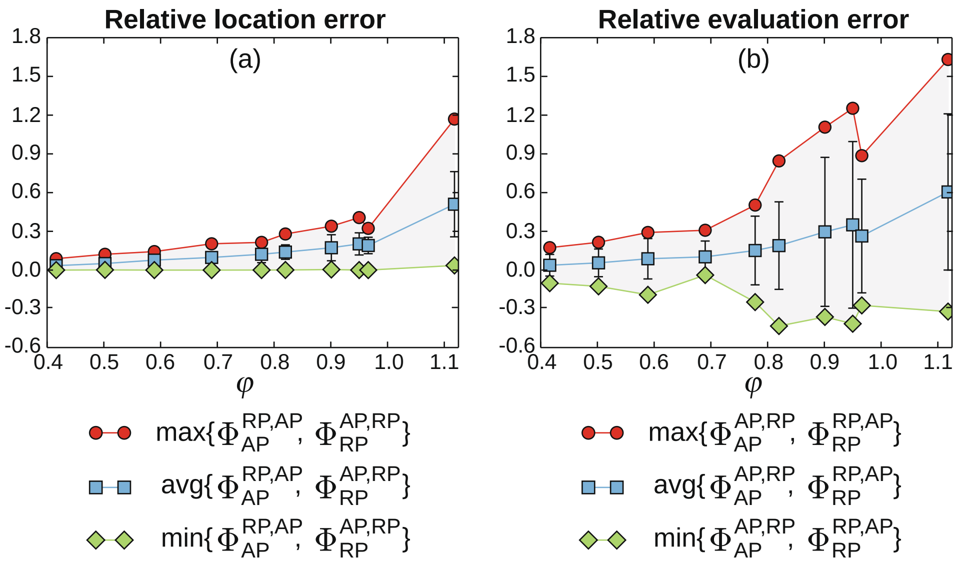

Figure 6. The maximal, minimal and average relative location and evaluation errors as a function of the parameter φ. Maximum, minimum and average values are for a given φ (i.e. for a given district) calculated from the results of all experiments, where $p = 1, \ldots, 40$. Error bars are reflecting the standard deviation around the average.

used in the following way. If the designer knows all other important uncertainties in input data and if, for instance, the largest is the uncertainty in travel times that was estimated to 20%, than if she/he obtains for this geographical area $\varphi = 0.416$ or smaller, from the Figure 6 can be estimated the range of the relative location and evaluation errors. In this case, the corresponding maximal relative location error $\Phi_l^{k,l}$ for $\varphi = 0.416$ is below 10%. Because in this case, the estimated relative location error is significantly lower than the involved uncertainty in other types of input data, the designer could conclude that it is not necessary to take into account the effects of the spatio-temporal demand distribution in the design of this particular service system.

5. Conclusions

To design the optimal structure of a public service system is a complex task, where many factors can lead to hardly predictable outcomes. We built a detailed model from the publicly available data and to estimate the demand, we combined it with ambient and residential population grids. We computed large number of optimal designs of a hypothetical public service system and from the numerical experiments we derived the following main conclusions:

- Use of the RP grid has a tendency to lower the value of the objective function systematically and thus the travel times from customers to the closest service centres can be easily underestimated. This result is important, because due to the better availability of residential population data, there is a tendency to use residential data in the location analyses independently on the application Burkey *et al.* (2012), Janáček *et al.* (2012), Nordbeck *et al.* (2013).
- Our analyses give evidence that the public service system designers should be more careful when evaluating the efficiency of existing systems. Errors that are associated

with the evaluation of already located facilities have tendency to exceed the errors that emerge when searching for efficient location of facilities.

- The average and the maximum location and evaluation errors grow in a non-linear way as the measure of distance between population grids is increasing. This dependence can be used to assess the size of errors associated with the demand model that can be compared with other input parameters and help to designers to decide which errors to account for.

It is important to note that although our study is based on the best available population data, these data describe the reality only to some limited extent. Our results also give evidence that more efforts, which should result in bottom-up population data for the Slovak Republic, are needed. Currently, freely available high-quality population data for the Slovak Republic, but also some other European countries, do not entirely match the needs for the public service system design. Open data initiatives and recent advances in obtaining population densities from on-line social networks Tarasov *et al.* (2013) or mobile phone data Walsh and Pozdnukhov (2011) are thus in this sense very promising.

Supporting information

File S1 Supplementary information file which includes supplementary figures.

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SUPPLEMENTARY INFORMATION

Effects of demand estimates on the evaluation and optimality of service centre locations

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1. Quality of the OSM road network

To the best of our knowledge, currently there is no study that evaluates a quality of OSM road network for the area of the Slovak Republic. For the analyses presented in the main paper, the information about the travel times between pairs of DPs is crucial. Hence, when evaluating the quality of the road network, we can restrict ourselves only to this aspect. Here, we compare OSM with HERE Maps (previously known as OVI Maps or Nokia Maps, www.here.com). HERE Maps enables to obtain the shortest paths and travel times between pairs of road network vertices.

It is not publicly known how the travel times are estimated by HERE Maps. Therefore, we decided to compare lengths of the shortest paths. For each selected district (see Table 1 of the main paper), we randomly selected 1000 different pairs of the road network vertices. Origin and destination vertices were always chosen from two different municipalities. We calculated the shortest path length between them using OSM data. Using the geographical coordinates, we entered both nodes into HERE Maps and we calculated the shortest path. Average values of the absolute differences between lengths of both shortest paths are displayed in Figure 1.

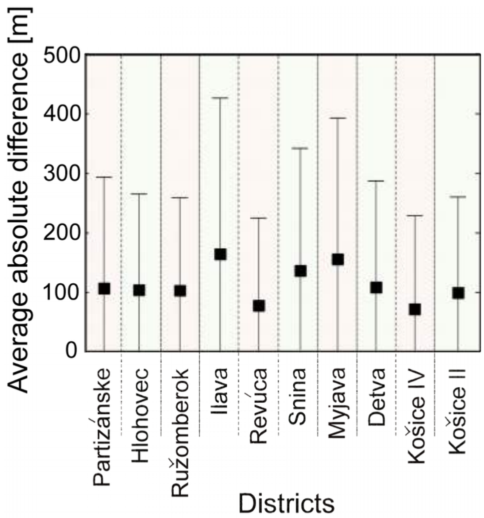

Figure 1. Average of absolute differences between lengths of shortest paths calculated from OSM road network and obtained from HERE Maps. Average is taken over 1000 node pairs in each district. Error bars are reflecting the standard deviation around the average.

The average absolute difference is for all selected districts less than 180 meters and in the majority of districts it is within 110 meters. Because we generated data models considering square cells 100×100 metres, we conclude that the level of agreement between OSM and HERE Maps is sufficient for the purposes of this paper.

It should be also noted that existing differences are not inevitably caused by errors in OSM data. When analysing the cases with the largest absolute differences, we identified two classes of problems causing differences between paths. The first source of inconsistencies is in the routing algorithm. HERE Maps uses an advanced routing algorithm that can, to some extent, consider the traffic rules. We used the classical Dijkstra algorithm on the OSM road network, which allows changing the direction when it is permitted by the directed graph that represents the road network. The second source of differences is in the quality of the OSM and HERE Maps road networks. Lower quality of road networks we find in rural areas. We found many small villages that differ in the completeness of the road network. While some areas are better covered in OSM, some other are better in HERE Maps. Therefore, it is hard to conclude clearly, which road network is more complete.

Although it was very rare, we also found some disagreements in the road segment classes in rural areas. We identified several apparent problems in both data sets. Occasionally, a missing minor road segment (forest, dirty or field road) was leading to a large difference in the shortest paths length. We identified five situations of missing minor road segment in HERE Maps and three missing minor road segments in OSM data leading to the absolute difference larger than 1 km. We eliminated such cases from the analysis as outliers, because we do not expect emergency public systems vehicles using such road segments and thus these cases would lead to misleading distortions in the results.

2. Comparison of Residential and Ambient Population Grids

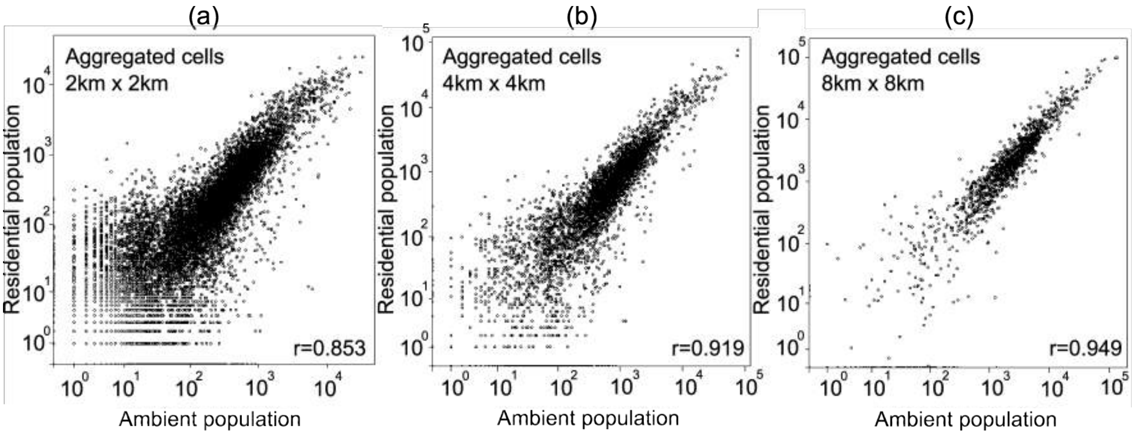

Figure 2. Scatter plot of the cell population comparing AP and RP grids for the area of the Slovak Republic using the resolution of (a) 2×2 km, (b) 4×4 km and (c) 8×8 km. Pearson product-moment correlation coefficient between population values attributed to individual grid cells we denote as *r*.

3. Complete Results of Numerical Experiments

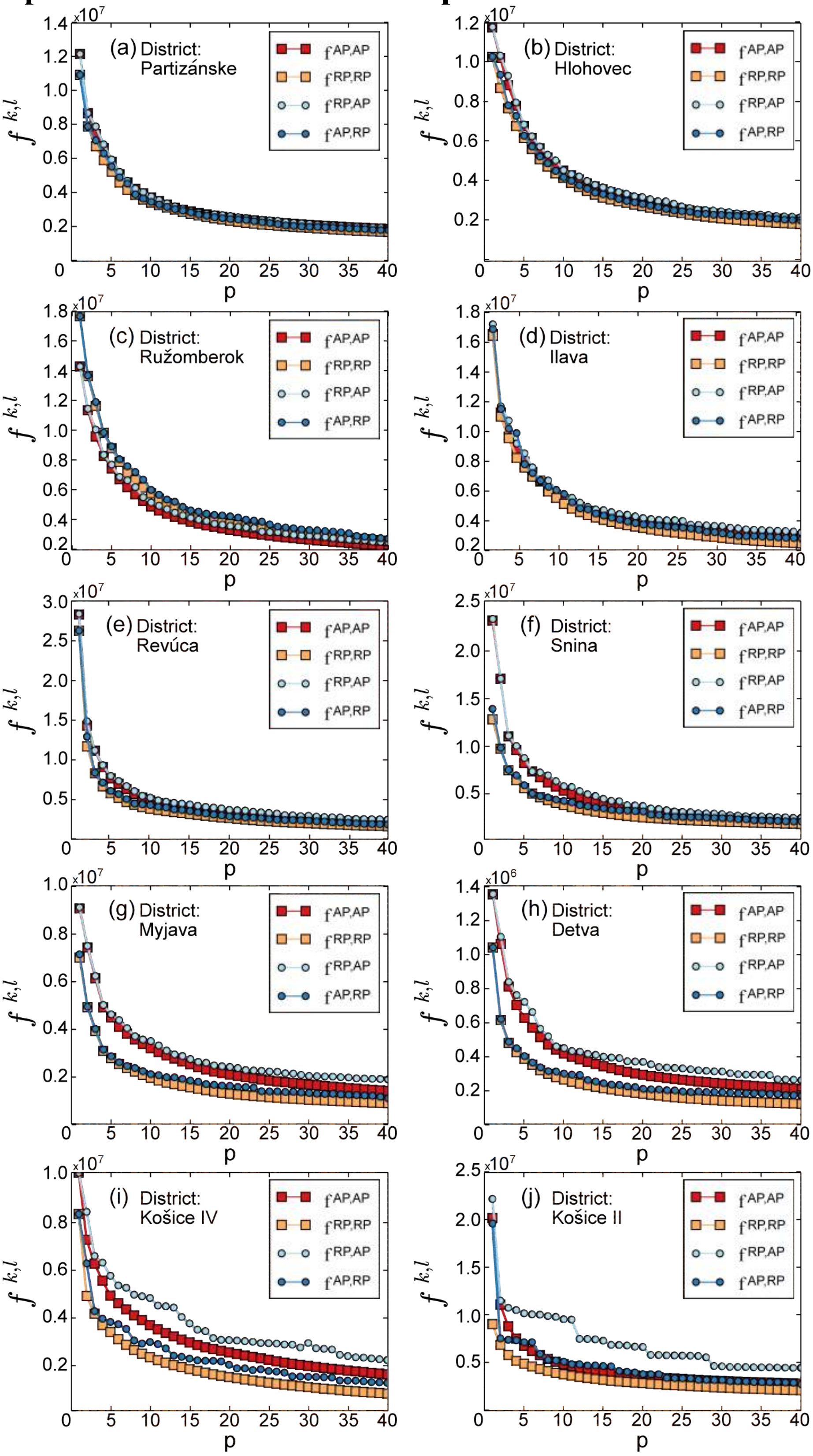

Figure 3. The sum of weighted travel times in seconds from DPs to the closest service centre (objective function value) as a function of the number of located service centres p. More detailed information about selected districts is given in Table 1 of the main paper.

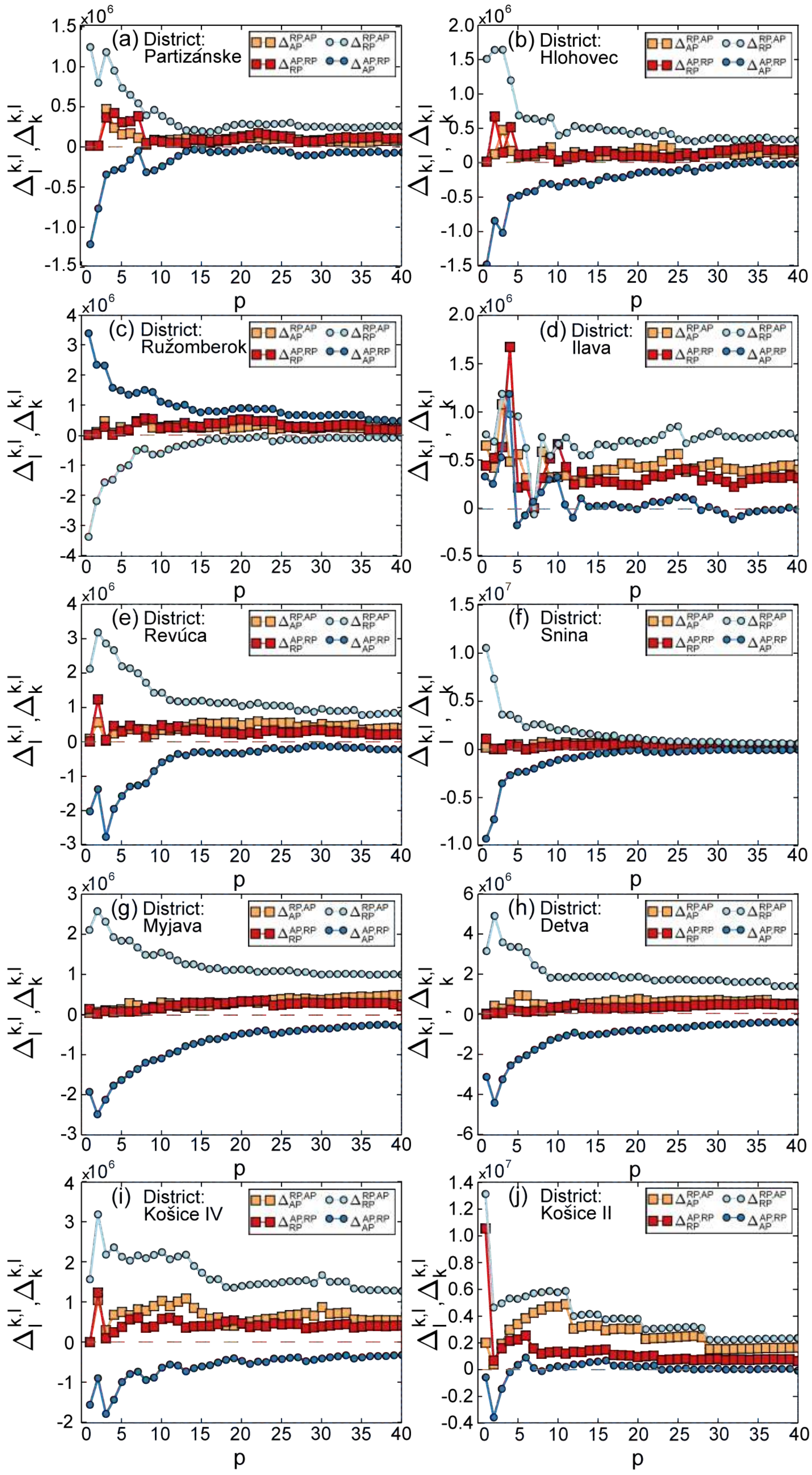

Figure 4. Absolute location and evaluation errors measured for ten selected districts, caused by the interchange of population grids as a function of the number of located service centres *p*. More detailed information about selected districts is given in Table 1 of the main paper.

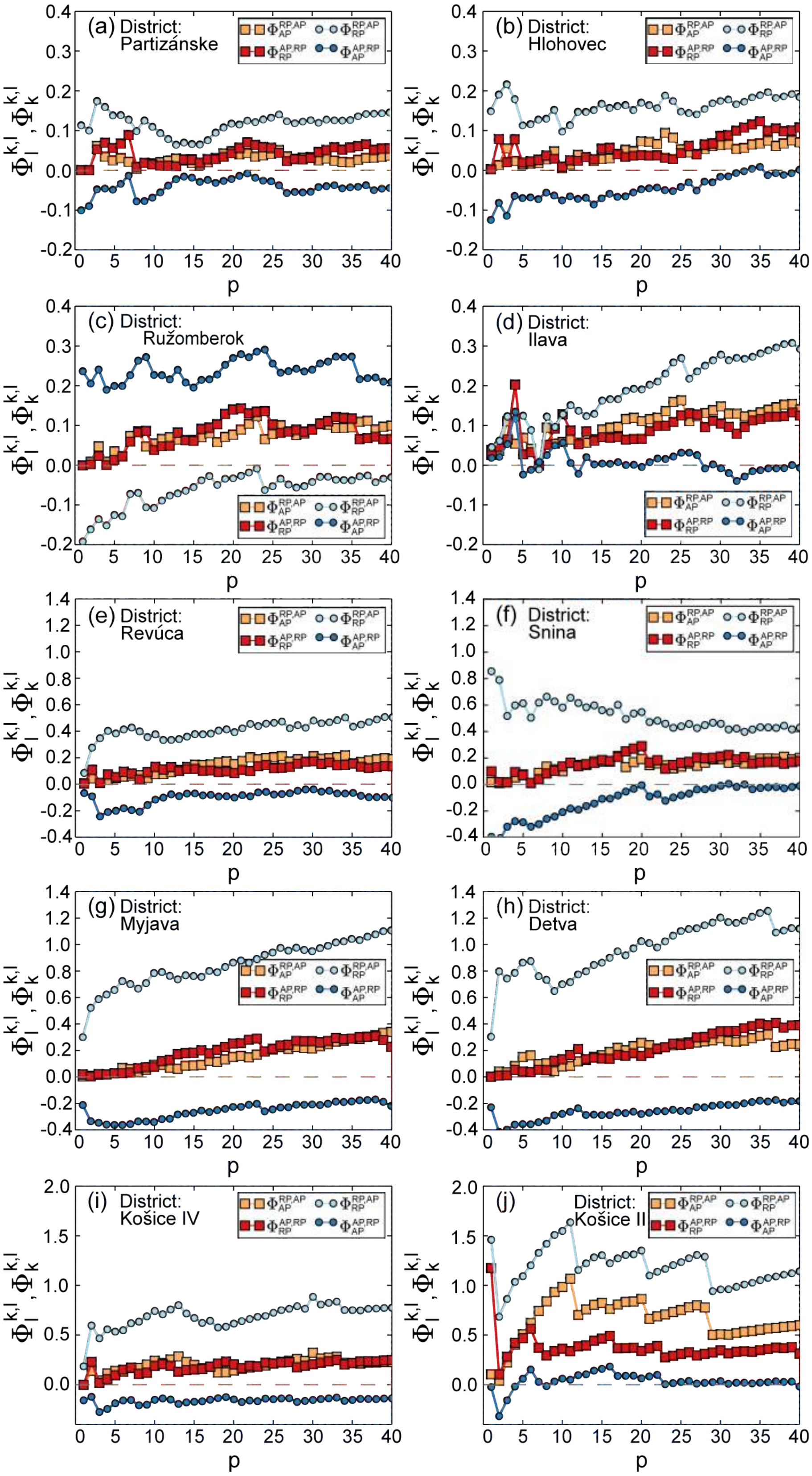

Figure 5. Relative location and evaluation errors measured for ten selected districts, caused by the interchange of population grids as a function of the number of located service centres p. More detailed information about selected districts is given in Table 1 of the main paper.

4. Choropleth maps of Partizánske and Košice II districts

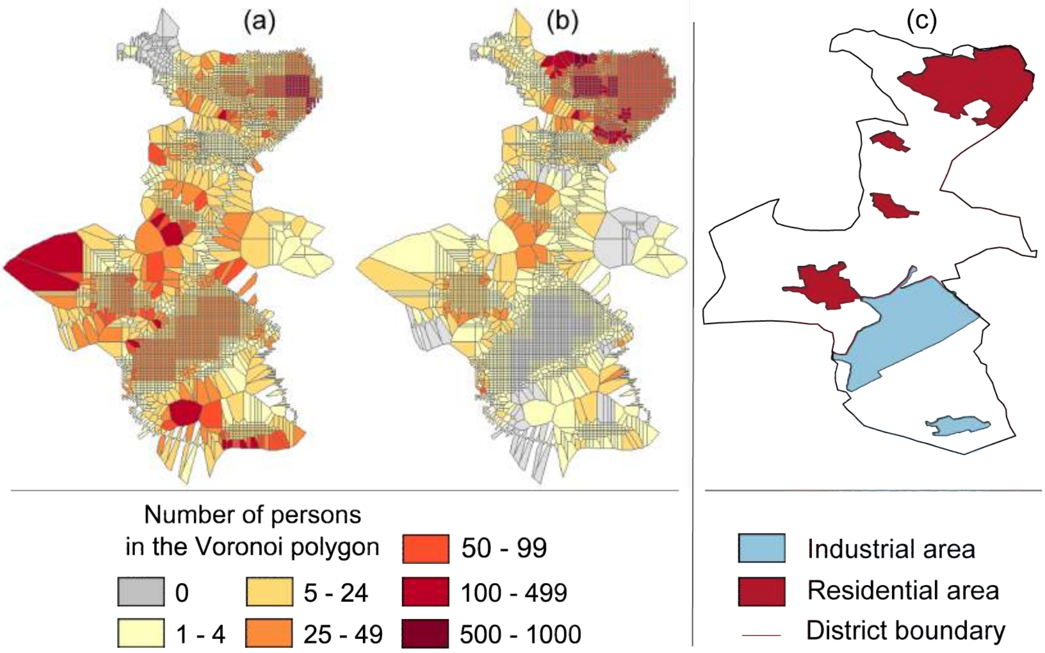

Figure 6. Choropleth map of the population of the district Košice II that is associated to the Voronoi polygons that are generated from the positions of DPs. (a) AP population. (b) RP population. (c) Illustration of residential and industrial areas (source: CORINE Land Cover 2006).

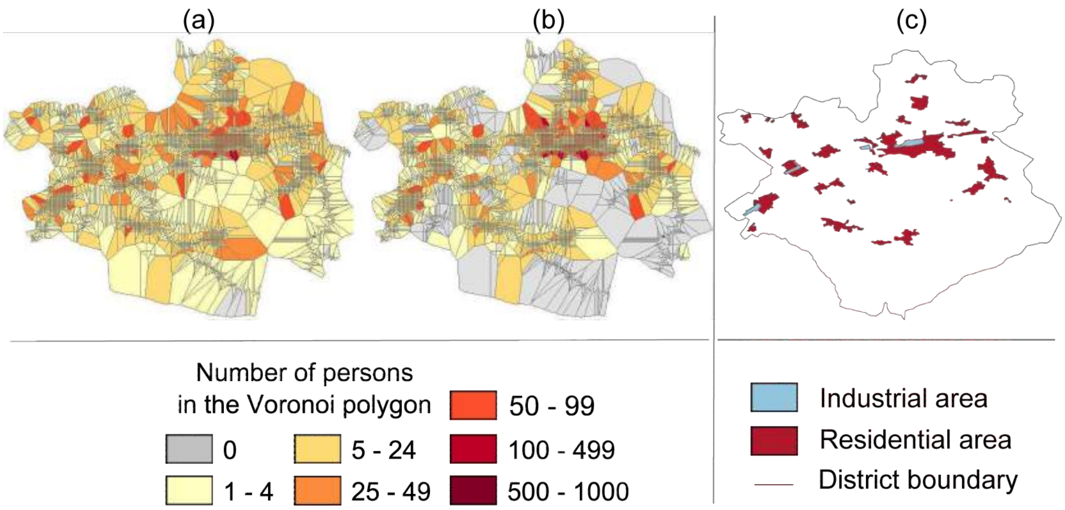

Figure 7. Choropleth map of the population of the district Partizánske that is associated to the Voronoi polygons that are generated from the positions of DPs. (a) AP population. (b) RP population. (c) Illustration of residential and industrial areas (source: CORINE Land Cover 2006).

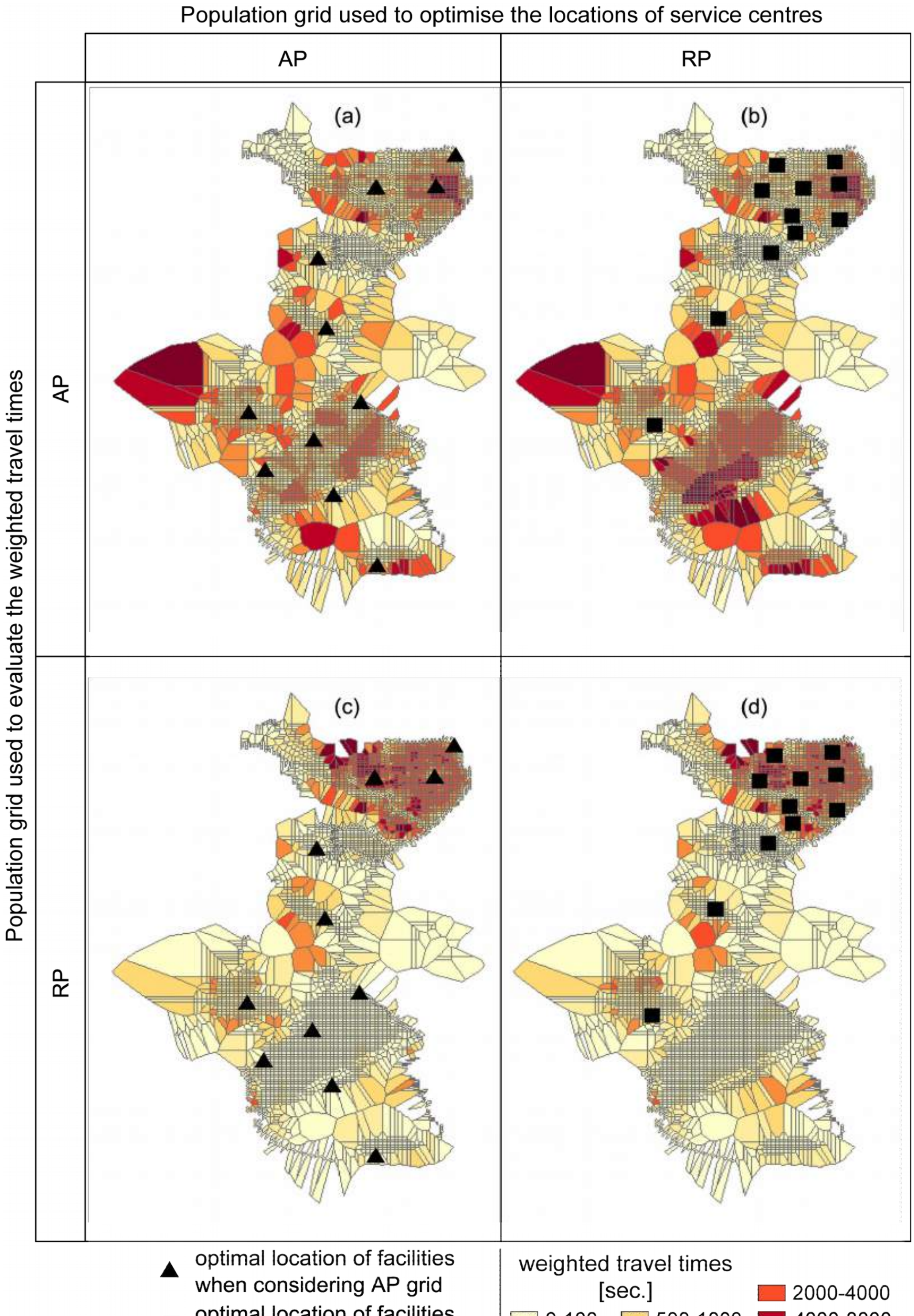

Figure 8. Choropleth map of weighted travel times from DPs to the closest service centre in the district of Košice II. In the first column, the locations of service centres are optimised with respect to the AP grid, whereas in the second column the locations of service centres are optimised with respect to the RP grid. In the first row, we evaluate the shortest travel times on the road network between DPs and closest service centres considering AP grid, while in the second row we evaluate the shortest travel times on the road network between DPs and closest service centres considering RP grid.

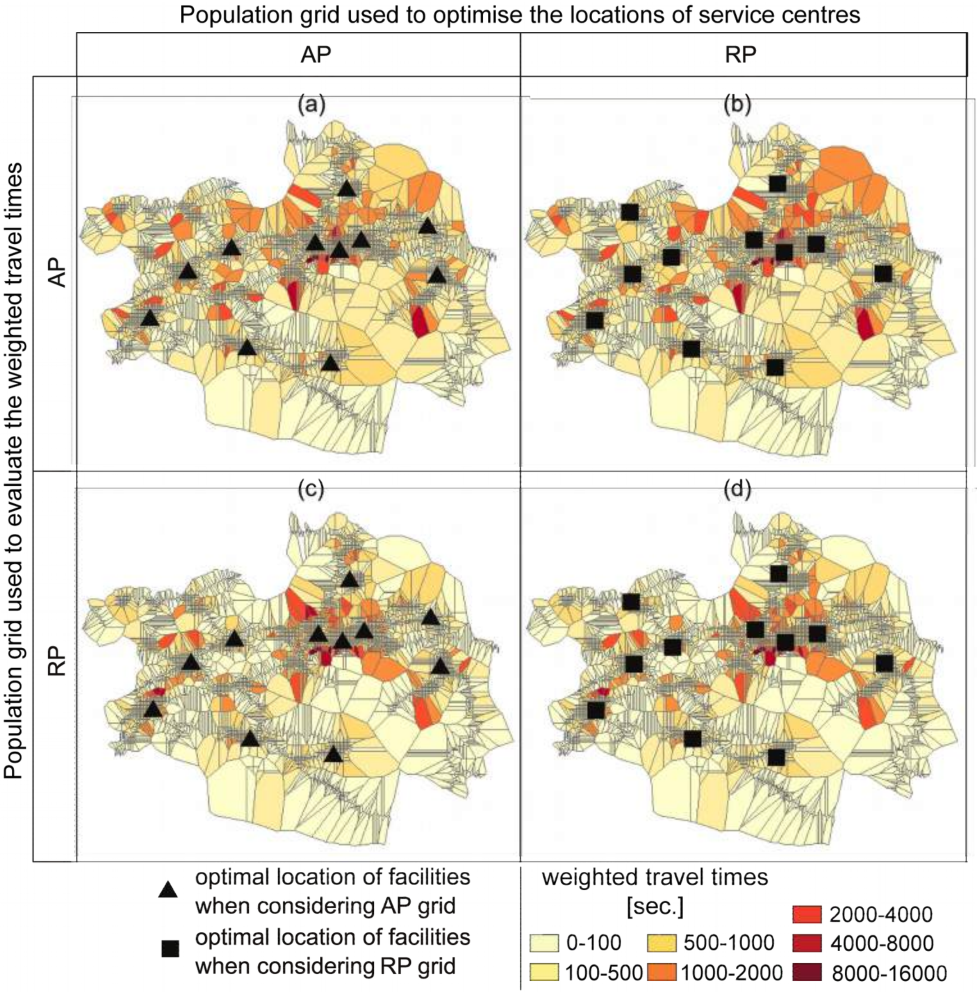

Figure 9. Choropleth map of weighted travel times from DPs to the closest service centre in the district of Partizánske. In the first column, the locations of service centres are optimized with respect to the AP grid, whereas in the second column the locations of service centres are optimized with respect to the RP grid. In the first row, we evaluate the shortest travel times on the road network between DPs and closest service centres considering AP grid, while in the second row we evaluate the the shortest travel times on the road network between DPs and closest service centres considering RP grid.

Acknowledgement

This product was made utilising the LandScan (2012) High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set. Neither UT-BATTELLE, LLC NOR THE UNITED STATES DEPARTMENT OF ENERGY, NOR ANY OF THEIR EMPLOYEES, MAKES ANY WARRANTY, EXPRESS OR IMPLIED, OR ASSUMES ANY LEGAL LIABILITY OR RESPONSIBILITY FOR THE ACCURACY, COMPLETENESS, OR USEFULNESS OF THE DATA SET.

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