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Defining usual environment with mobile tracking data

Janika Raun, Rein Ahas

Department of Geography, University of Tartu, Estonia

janika.raun@ut.ee

rein.ahas@ut.ee

ABSTRACT

Domestic tourism is an important part of tourism economy, but it is difficult to measure it as it is defined by travelling outside of usual environment. The aim of this study is to provide a new way for determining usual environment based on mobile positioning and GPS data. We measure domestic visitors' spatiotemporal behaviour with passive mobile positioning data, containing Call Detail Records (CDR) from mobile network operators about the times and places of call activities, and smartphone based GPS tracking data together with a questionnaire containing qualitative information about individuals' activity places. Different methods (anchor point model, administrative units) for determining the usual environment are used and compared. Results indicate that the number of domestic trips is dependent on the size of the unit used as usual environment.

Keywords: domestic tourism, usual environment; mobile positioning, GPS

1. Introduction

The three basic forms of tourism are outbound, inbound and domestic tourism. The first two, are relatively well studied on both national and international level, using different border crossing and accommodation statistics; the latter however, is insufficiently studied. There are relatively few studies focusing on residents travelling within their own countries, although it is by far the most common form of travel. The reason behind it lies in the definition of tourism. According to the European Union regulation (No 692/2011) concerning European statistics on tourism, *'tourism' means the activity of visitors taking a trip to a main destination outside their usual environment, /---/"*. Therefore, defining and measuring *'usual environment*' is crucial for tourism research.

Usual environment is defined *"as the geographical area (though not necessarily a contiguous one) within which an individual conducts his/her regular life routines"* (IRTS, 2008). Tourism experts and national statistics from all over the world have tried to find a consensus on determining the concept, but the result is that no strict framework can be drawn and the definition varies by countries and individuals (IRTS, 2008; Eurostat, 2014). Nevertheless, there are recommendations suggesting that the determination of usual environment should be based on the following criteria: frequency of the trip; duration of the trip; the crossing of administrative or national borders; distance from the place of usual residence (IRTS, 2008; Eurostat, 2014); and the purpose of the visit (European Union regulation No 692/2011).

Therefore, the threshold for usual environment has been set variously in different countries. For example, in order to be a domestic tourist in New Zealand one needs to travel by a scheduled flight or inter-island ferry service; or travel more than 40 kilometres from their residence (one way) (Statistics New Zealand, 2014). Govers and his colleagues (2008) point out that this kind of distance approach lacks theoretical embedding as *"the 'usual environment' consists of a selection of places, rather than one space with come concentric boundary"*. In an Austrian CATI survey the interpretation of the usual environment is left to the subjective feeling of the respondent (Eurostat, 2014).

Previous studies and statistical overviews have mainly used accommodation statistics, household surveys, trip diaries and interviews in order to analyse domestic tourism trips taken. Due to the rapid development of information and communication technologies (ICT) in recent decades, various tracking datasets have been applied to the study of tourism and tourist movements, including mobile positioning data (e.g., Ahas, Aasa, Roose, Mark, & Silm, 2008; Calabrese & Ratti, 2006; Nilbe, Ahas, & Silm, 2014, Raun, Ahas, & Tiru, 2016), GPS data (e.g., Grinberger, Shoval, & McKercher, 2014; Shoval & Isaacson, 2007; Shoval, McKercher, Ng, & Birenboim, 2011), Bluetooth data (e.g., Versichele et al., 2014; Yoshimura et al., 2014), user-generated data such as geo-located tweets from Twitter (e.g., Hawelka et al., 2014), and geo-referenced photos from the photo-sharing webpage Flickr (e.g., Girardin, Fiore, Ratti, & Blat, 2008).

Compared with traditional accommodation and survey data, tracking technologies enable to study tourism more precisely and effectively because (a) the spatial and temporal accuracy of the data are better; (b) the tracking periods are longer; (c) tracking allows us to follow a tourist throughout his/her visit; and (d) digital data collection and processing are easy and timeliness (Raun, Ahas, & Tiru, 2016). In this paper we present possibilities to use mobile positioning data and GPS data for defining usual environment and measuring domestic tourism. We introduce alternative ways for determining usual environment based on mobile positioning and GPS data in Estonia.

2. Measuring usual environment with passive mobile positioning data

Database used in current study consists of the call activities (CDR) made by 8700 randomly chosen people from Estonia during the year 2014. The distribution of home anchor points of our sample correlates to the overall population distribution into counties in Estonia. In order to analyse the movement of people we only included the 8 128 213 call activities that were made during trips. This means that all of those call activities that were done in people's home anchor points are not included in this study. As the aim of this study is to investigate domestic tourism trips we have also excluded all those trips that were made abroad (N=19203).

During the study year 8700 people made 1 325 260 trips inside Estonia. On average one person made 152 trips per year, median is 128. The timing and duration of trips were calculated based on the time of call activities. 72% of the trips were one day trips which means there were not an overnight stay. Further on in the analysis we have divided the trips into short (one day) and long (two or more days) trips. Trips were distributed into months according to the time of the first call activity in a trip. Hence the maximum number of trips was made in May and minimum in February.

In order to analyse the number of possible domestic tourism trips taken, we divided the trips into three main categories: (a) trips made inside home municipality; (b) trips made outside of home municipality; and (c) trips made outside of home county. The distribution of the trips is shown in table 1. The first category constitutes more than half of all the trips made (N=680 509). It can be described by everyday movements, as 80% of those trips do not include an overnight stay. In the second case we can already see the increase in the share of long trips up to 36%. The third group, trips outside of home county, can be seen also as a subgroup of the previous one, as the trips are made outside of home municipality, but they have also crossed the county border. In this case the long trips already constitute 56%.

Table 1. The distribution of trips based on their spatial extent category and trip duration.

Trip category	**Trip duration**				Total (N)
	One day trips (N)	Percentage (%)	Two or more days (N)	Percentage (%)	
Trips inside home municipality	547 115	80.4	133 394	19.6	680 509
Trips outside of home municipality	410 696	63.7	234 055	36.3	644 751
Trips outside of home county	69 511	43.6	89 813	56.4	159 324
Total number of trips	957 811	72.3	367 449	27.7	1 325 260

Besides just looking the number of trips made outside of home municipality and parish we included the information about the regular places of each person. This means that we took into account only those trips that were made outside of home county and excluded the trips that were related to visiting work time, second home or other regular anchor point. Therefore, the number of trips that could be related to tourism declined from 159 324 to 31 478 which included 69 511 one-day visits and 89 813 trips lasted longer than one day.

3. Measuring usual environment with smartphone based GPS data

GPS data used in current study is collected through an Android based smartphone application named YouSense. The YouSense application runs on the participants' phones, and records events of interest when they happen, not on a regular schedule (Linnap & Rice, 2014). In addition to the collection of GPS data interviews were done to understand the meaning of regularly visited places.

There are many different empirical ways to measure usual environment based on GPS data. We can draw parallels from measuring daily or monthly activity space, where confidence ellipse, kernel density estimates, shortest paths networks (Schönfelder & Axhausen 2003); minimum convex hull or polygon approach (Buliung & Kanaroglou, 2006; Buliung & Remmel, 2008) are being used. In our study we used administrative borders and Kernel densities to use visual analytical tools for mapping usual environment and domestic tourism (Figure 1).

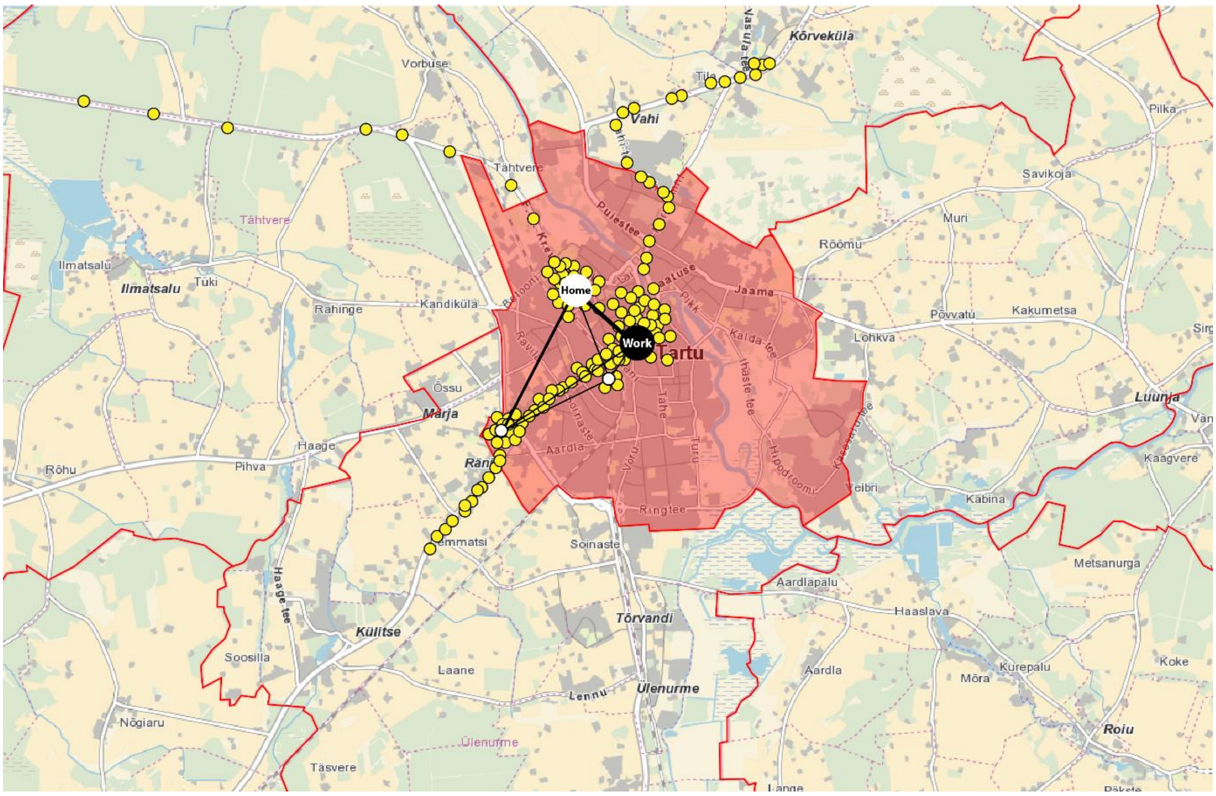

Figure 1. Measuring usual environment based on administrative borders of home city Tartu from Smartphone based GPS data of one user during one week in 2014.

In our study we used Kernel densities to illustrate the seasonal changes in usual environment (Figure 2). Differences were most distinct in summer months were people tend to spend more time in their summer houses. Therefore, it is important to take into account whether to analyse the overall movements in whole year or to look at also the seasonal changes.

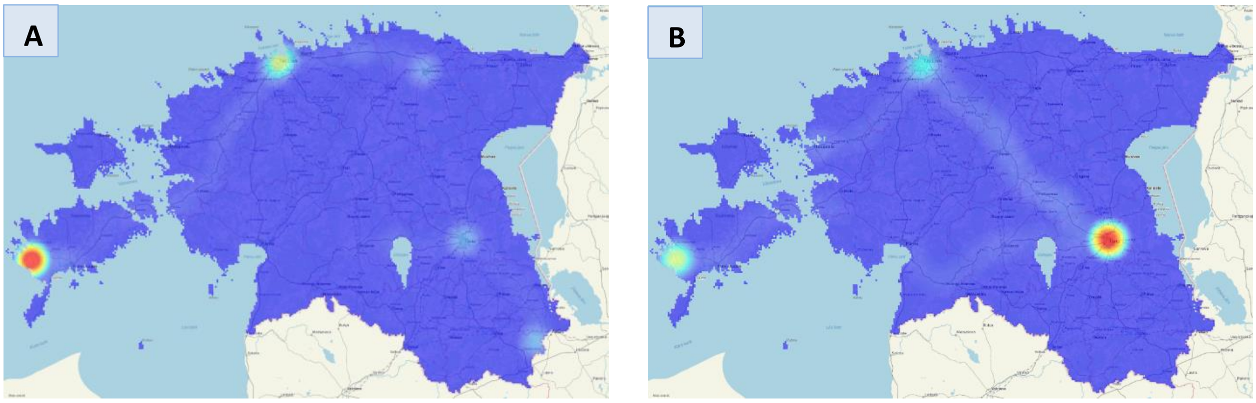

Figure 2. Seasonal changes in activity patterns in July (A) and in September (B) based on one month's Smartphone based GPS data in 2014 of one user.

4. Discussion and Conclusions

The comparison of different datasets indicates that passive mobile positioning data is a good data source because of the high number of respondents (exhaustive in scope) (Kitchin, 2013) and fast data processing cycle (Eurostat, 2014). Nevertheless, CDR data is fragmented, spatial accuracy is only on the network cell level and access to the data is limited (Eurostat, 2014). Therefore, it is complicated to measure exact usual environment because of the low spatial accuracy of passive mobile positioning data. Another concern is that we do not know any information about the meanings of the trips. Regardless, filtering such exhaustive databases can give new understandings of domestic spatial mobility and the overall potential of domestic tourism.

Smartphone based GPS data together with a questionnaire is spatially more accurate than mobile positioning and gives more possibilities for determining usual environment, as we have additional information about the respondents and their trips. This in turn becomes a disadvantage as the number of respondents cannot be very high. The apps have to be downloaded to respondents' phones or new smartphones must be distributed, that comes at high cost and additional interviews are time consuming.

The advantages of using tracking datasets lie in the possibilities to empirically measure people's usual environment based on their actual behaviour and thereby analyse the domestic trips taken. The main constraints are accessing the data and the question of privacy and data protection. Spatially and temporally precise movement data is a valuable input for measuring domestic tourism and this knowledge is helpful in destination marketing and management focusing on local visitors. Understanding and measuring people's everyday movement areas is an important task also in other live spheres like transportation, taxation, public administration etc.

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