

Smartphone GPS tracking—Inexpensive and efficient data collection on recreational movement

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Abstract

This research note describes the methodological and practical applications of using smartphone GPS tracking (SGT) to explore the spatial distribution and density of recreational movement in multiple-use urban forests. We present findings from the pilot phase of an ongoing case study in Keskuspuisto (Central park), Helsinki, Finland. The study employs an inventive and inexpensive approach for participatory data collection i.e. gathering GPS data from recreational users who have already recorded their routes for purposes other than research, using any kind of sports tracking application on their personal mobile phones. We used the SGT data to examine visitor spatial patterns on formal trails and informal paths, and present examples with runners and mountain bikers. Hotspot mapping of mountain bikers' off-trail movement was conducted identifying several locations with clustering of off-trail use. Small-scale field mapping of three hotspot areas confirmed that the method accurately located areas of high use intensity where visible effects of path widening and high level of wear on the forest floor vegetation could be observed. We conclude that the SGT methodology offers great opportunities for gathering useful and up-to-date spatial

information for adaptive planning and management as it highlights areas where conservation and visitor management measures may need to be adjusted. We suggest that this method warrants testing also for other user-centred research and planning purposes.

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Body of manuscript

1. Introduction

Knowledge about visitor movement patterns is essential to planning and management that aims to balance various societal demands and preserve and protect natural resources (Beeco & Brown, 2013; Cole & Daniel, 2003; Orellana, Bregt, Ligtenberg, & Wachowicz, 2012). Advances in spatial technologies such as Global Positioning Systems (GPS) and Geographic Information Systems (GIS) have proven to be useful tools to better plan, manage and monitor recreational use in multiple-use natural areas (Beeco, Hallo, & Brownlee, 2014; de Vries & Goossen, 2002; Wolf, Wohlfart, Brown, & Bartolomé Lasa, 2015). GPS tracking has been increasingly used to study human movement patterns in a variety of natural resource applications such as park and protected area management, tourism and outdoor recreation (e.g. D'Antonio et al., 2010; J. C. Hallo et al., 2012; Meijles, de Bakker, Groote, & Barske, 2013). Previous studies have showed great potential of the method to gather accurate and detailed spatial data on the distribution and intensity of use while capturing actual movement behaviour on and off the formal trail network (Taczanowska, Muhar, & Brandenburg, 2008; Wolf, Hagenloh, & Croft, 2012). Off-trail movement creates spontaneous path systems making it difficult to predict where and when visitor impacts occur. From a management perspective this process can be hard to control or reverse, therefore up-to-date understanding of the creation of informal paths is crucial for managing recreational impacts.

A common practice in GPS tracking studies of outdoor recreation in natural areas is to hand out a GPS device to participants, which bears several disadvantages such as high equipment investment costs, concerns with retrieval of units and possibly affecting human spatial behaviour due to participants' awareness of the device (O'Connor, Zerger, & Itami, 2005;

Wolf et al., 2012). Using GPS-enabled mobile phones (i.e. smartphones) to collect route data is another, relatively new, but rapidly advancing technique used in research. In urban settings, smartphone GPS tracking (SGT) has been employed mainly in transportation and mobility studies e.g. for creating road inventories or analysing transportation modes and popular routes (Higuera de Frutos & Castro, 2014; Hood, Sall, & Charlton, 2011; Nitsche, Widhalm, Breuss, Brändle, & Maurer, 2014). Data is usually collected by providing study participants with mobile phone devices or using a designated software application for the specific research purpose. On the other hand, the rapid emergence and increasing popularity of volunteered geographic information (VGI) presents new opportunities for research as citizens are actively engaged in the use and production of geographic information driven by individual or community interests (Feick & Roche, 2013; Goodchild, 2007). Using sports tracking applications can be seen as such activity as data is voluntarily generated and often shared in online platforms for different personal reasons e.g. to monitor health and fitness performance, share routes, experiences and photos, guided by self-promotion or social reward that are common motivations for contribution in VGI (Oksanen, Bergman, Sainio, & Westerholm, 2015). This can be also described as self-tracking (in some studies referred to as ‘participatory sensing’ (Burke et al., 2006) and ‘self-surveillance’ (Albrechtslund & Lauritsen, 2013)) of individuals who use mobile phones to gather and share various data on their everyday lives, routes or environment. Here we aim to contribute to this growing area of research by illustrating the utility of available, voluntarily collected smartphone GPS self-tracking data for applications in urban forest management. The study employs an inventive and low-cost approach for participatory data collection i.e. gathering movement data from recreational users who have already recorded their routes for purposes other than research, using any kind of sports tracking application on their personal mobile phones.

This research note reports on the pilot phase of a larger on-going empirical study in Helsinki's Keskuspuisto (Central Park). The overall goal of this paper is to: 1) demonstrate the use of SGT for examining spatial patterns and density of recreational movement and 2) outline the potential and limitations of the method based on our pilot data. More specifically, the aim is to test whether the method can be used to locate movement on formal trails and informal paths, identify hotspots of heavy off-trail use, and to validate the accuracy and usefulness of the SGT data by observing path and vegetation wear on site.

2. Methods

2.1 Study area

Keskuspuisto is the largest single green area and one of the seven "Green Fingers" in the city of Helsinki, Southern Finland (hemi-boreal vegetation zone; population of 620 715 (Statistics Finland, 2014)). Over 10 km in length and up to one km wide, it includes 100 km of formal trails (City of Helsinki Urban Facts, 2005). Keskuspuisto covers 1 100 ha of land, with several nature protection areas and 700 ha of old-growth forest (City of Helsinki Urban Facts, 2005). It is a multiple-use urban forest offering opportunities for a range of outdoor activities (e.g. walking, dog-walking, jogging, cycling, horse-riding, mountain biking, mushroom picking, observing nature and skiing), as well as for commuting. It is intensively used with over two million yearly visits (Ilvesniemi & Saukkonen, 2013).

2.2 Data collection and analysis

The pilot phase of this study, conducted in collaboration with Public Works Department of City of Helsinki, began in summer 2014 when GPS route data was gathered from volunteers who used any sports tracking application (e.g. Sports Tracker, Strava) on their personal smartphones. Participants were recruited both on-site (approaching visitors inside

Keskuspuisto) and online (contacting users who had shared routes on the Sports Tracker website). The study was carried out in accordance with the principles of informed consent i.e. all volunteers were asked to sign a letter of “Consent to Participate in Research” (available both in English and Finnish) providing clear terms and conditions of participation. Furthermore, to address privacy issues related to using SGT data, personal identifying information (name and email) was processed so as to guarantee confidentiality and anonymity i.e. no individual could be recognized from the study results. Finally, only those parts of the GPS tracks within the boundaries of Keskuspuisto (intra-site tracks) were used so that human subjects cannot be traced to home, work or other location outside of the study site.

We did not hand out GPS units/phone devices or use a designated tracking application; instead we explored the usefulness of data that was already collected by recreational users for other purposes than research. When sending their GPS tracks by email, participants were asked about their socio-cultural background (sex, age, education and occupation), the type of recreational activity and whether they had used formal trails or informal paths during that particular visit.

Analysis and validation of the collected GPS route data were conducted in the following sequence:

- 1) Estimating the GPS positioning accuracy
- 2) Buffer analysis to distinguish movement on formal trails and informal paths, and to explore spatial patterns of different recreational groups
- 3) Density analysis to locate hotspots of off-trail movement
- 4) Small-scale field mapping to validate the results of the hotspot analysis

Participants' GPS tracks were imported in ArcGIS (v.10.2.1) in two different formats (lines and points) to allow for different types of analysis and then cut according to the study area borders. Intra-site tracks were grouped by recreational activity (runners, mountain bikers, walkers, dog-walkers etc.) and then analysed for their distribution on formal trails (paths designated and/or maintained by authorities) and informal paths (visitor-created paths).

The first step was to estimate the accuracy of the GPS track data. Today's mobile phone devices incorporate basic GPS receivers that need at least four independent satellite measurements to locate a fixed position (Bauer, 2013). The GPS positioning accuracy could be affected by a variety of factors: environmental characteristics (terrain, built structures, tree canopy) (Lai, Li, Chan, & Kwong, 2007), space weather conditions (Kos & Brčić, 2013), the mobile phone device and its operating system (Hess, Farahani, Tschirschnitz, & von Reischach, 2012), the use of integrated sensors (e.g. accelerometer and compass) (Mok, Retscher, & Wen, 2012) and assisting location technologies (Cell ID and WLAN), and the sports tracking application (Bauer, 2013). Sports tracking applications employ regular sampling of movement data i.e. location fixes are acquired at even time intervals (approximately every second) (Long & Nelson, 2013; Oksanen et al., 2015; Sainio, Westerholm, & Oksanen, 2015) collecting a large point dataset. Due to the high source variation and heterogeneity of GPS data in this study i.e. participants using different mobile phone devices, various sports tracking applications (Sport Tracker, Endomondo, Polar, Strava), tracking their routes at different times and activity speed, the approach here was to estimate average deviation of the GPS tracks from the formal trail network. The formal trail network data was acquired from two different spatial datasets - the topographic database of National Land Survey (NLS) of Finland (scale 1:10 000) and City of Helsinki Road Map (scale 1:5 000). Ideally, distance measurements should be calculated based on deviations from a reference point that is considered accurate. However, after visual comparison of aerial

images (in Google Earth), both datasets showed some differences and inconsistencies in location accuracy, as well as variation in mapping detail with NLS map displaying slightly more detail. Therefore, *Proximity analysis* in ArcGIS were conducted with both datasets in order to calculate the average distance of point data of all on-trail GPS tracks (from participants who stated to have followed formal trails) to the formal trail line features. Using *Generate Near Table* tool, the shortest distance of the GPS points to the trail line features was calculated (ArcGIS, 2016) within a search radius of 20 m, indicating an average deviation of 9 m (9.07 m for City of Helsinki trail map and 8.99 m for NLS trail map). Consequently, a 10 m buffer size along the formal trail network (we used NLS dataset as it provided more detail) was considered sufficient for further analysis (Fig.1). The GPS line data was then intersected with the buffered trail network to distinguish on-trail (within the buffer) from off-trail movement (outside the buffer).

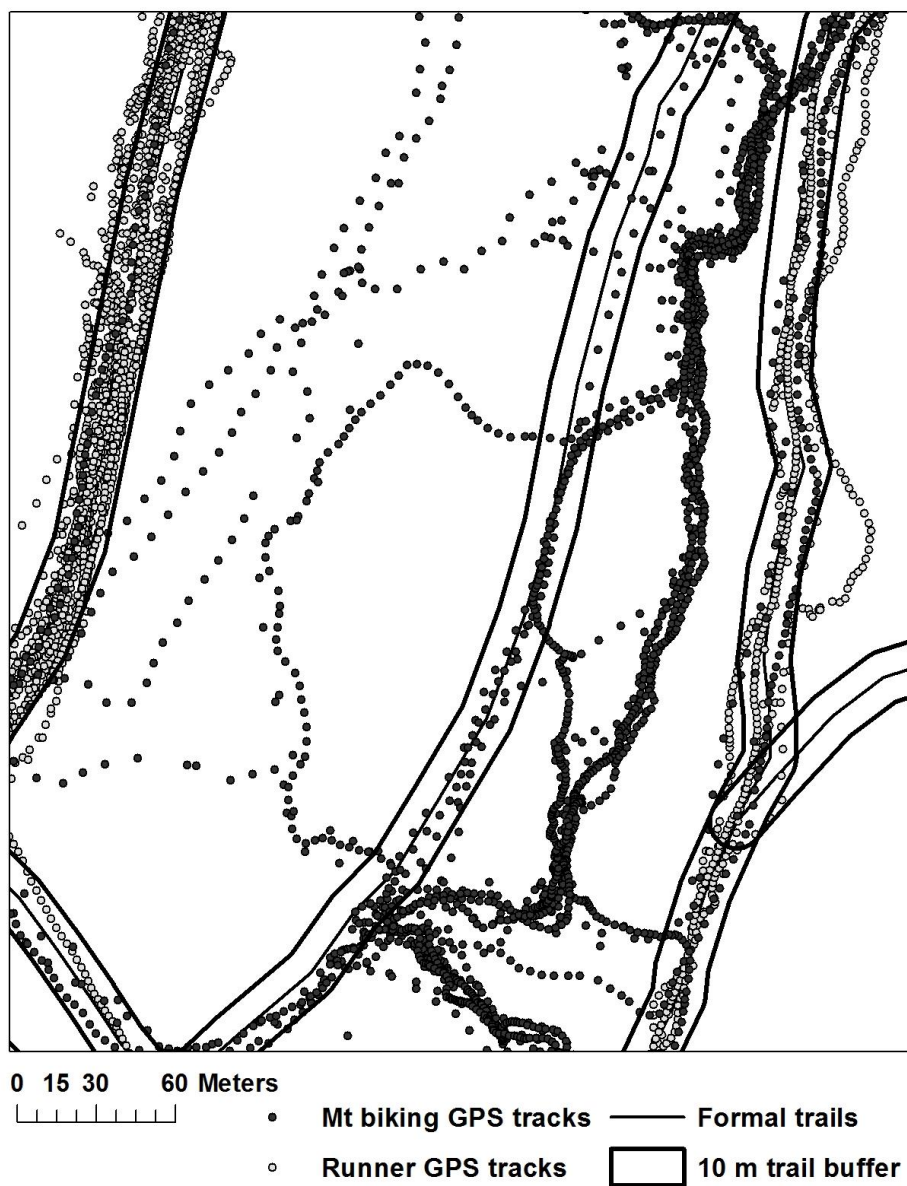


Fig. 1 A segment of typical GPS tracks and the 10 m formal trail buffer. Formal trail network available from National Land Survey of Finland.

The resulting maps helped to relate observed movement patterns to different user groups, however, during this pilot phase data was sufficient only for runners and mountain bikers. Mountain bikers clearly displayed more evident off-trail behaviour (for detailed results and % distribution of off-trail and on-trail movement, see the Results section). Thus, we conducted density analysis of mountain bikers' off-trail GPS tracks using kernel density estimation (KDE) (available in ArcGIS) to locate hotspots of heavy off-trail use. KDE is an established method for ecological or social applications in hotspot mapping (Alessa, Kliskey, & Brown, 2008; Lyon, Cottrell, Siikamäki, & Van Marwijk, 2011). We created a raster map using *Kernel Density Analysis* tool calculating the density of GPS line features in the neighbourhood of each raster cell (10 m x 10 m raster cell size) within a radius of 20 m. The tool creates smooth continuous surfaces surrounding each line based on a quadratic formula with highest value on the line moving towards zero at the end of the search radius (ArcGIS, 2016). Similar to previous studies (Alessa et al., 2008; Walden-Schreiner & Leung, 2013), we used a heuristic approach for selecting the 20 m search radius by testing different radius sizes to provide sufficiently detailed and clear visual representation. We used line data to avoid bias towards spatial clustering of GPS points due to participants standing still.

As a final step, we conducted fieldwork in May 2015 to validate the results of the hotspot mapping and provide ground evidence of the accuracy and effectiveness of the SGT methodology. Our hypothesis was that areas with high density of observed off-trail movement (i.e. hotspots) should display higher level of vegetation wear than areas with no observed off-trail movement (i.e. coldspots). To test this hypothesis, we first visually selected three of the most apparent hotspots in three different locations in Keskuspuisto: Pirkkola (hotspot area 1), Maunula North (hotspot area 2) and Maunula South (hotspot area 3) (Fig. 2b). The hotspot sample plots were then drawn in GIS as rectangular shapes to fit the size and shape of the hotspots in each area. The size of each sample plot was defined as follows: 500

m² (hotspot 1 and hotspot 2) and 300 m² (hotspot 3). Then, one coldspot sample plot was drawn in close proximity of each hotspot sample plot, with exactly the same size and shape as the focal hotspot. To allow for similar environmental conditions while avoiding subjectivity in sampling, we chose the first possible location for a coldspot plot using a clockwise rotation, starting from East to West, within 50 meters from the hotspot center. The criteria were that coldspots should portray no off-trail GPS tracks and neither should they overlay a maintained trail. Once on the field, the exact location of each hotspot/coldspot sample plot was identified using a GPS device and the borders were marked using a string. Similar to vegetation sampling methods used in previous studies (Hauru, Niemi, & Lehvavirta, 2012; Lehvavirta, 1999), the spatial distribution, width and level of wear of each path with visible signs of trampling (footprints, broken shoots, reduced cover etc.) and the level of wear of vegetation segments in each plot were measured. We sampled the level of wear using visual estimation with the following wear classification: 0 = untrampled vegetation, no visible effects of wear; 1 = visible effects of wear, vegetation damaged, but only slightly reduced in cover; 2 = visible effects of wear, vegetation damaged and reduced in cover, but not completely worn away; 3 = generally no vegetation on the path, humus layer not worn away, rocks and tree roots sometimes uncovered; 4 = bare mineral soil or a deeply worn humus layer, no vegetation remaining, rocks and tree roots often uncovered (Lehvavirta, 1999). The overall environmental characteristics of the sample plots were also estimated visually (Table 1).

3. Results

Data visualization

Altogether we collected 55 GPS tracks from participants (70% men and 30% women, 83% with higher education and 80 % in the 25-44 age groups) engaging in different recreational

activities. From this data, some preliminary spatial patterns could be identified for runners (25 GPS tracks) and mountain bikers (22 GPS tracks). Results from the buffer analysis indicated clear differences of how recreational movement of these groups is spatially distributed on formal trails and informal paths (Fig. 2 and 3a). Runners mainly followed formal trails with only 21% of the GPS tracks being off-trail, while 46% of mountain bikers' tracks were located outside the formal network. Interestingly, with such little amount of data, mountain bikers portrayed quite a structured movement pattern, concentrated along specific off-trail routes. The density analysis of mountain bikers' off-trail tracks located several areas with highest clustering of movement (i.e. hotspots) along these main off-trail routes (Fig.3b). Three of these hotspot areas were then sampled on the field (Fig.3b).

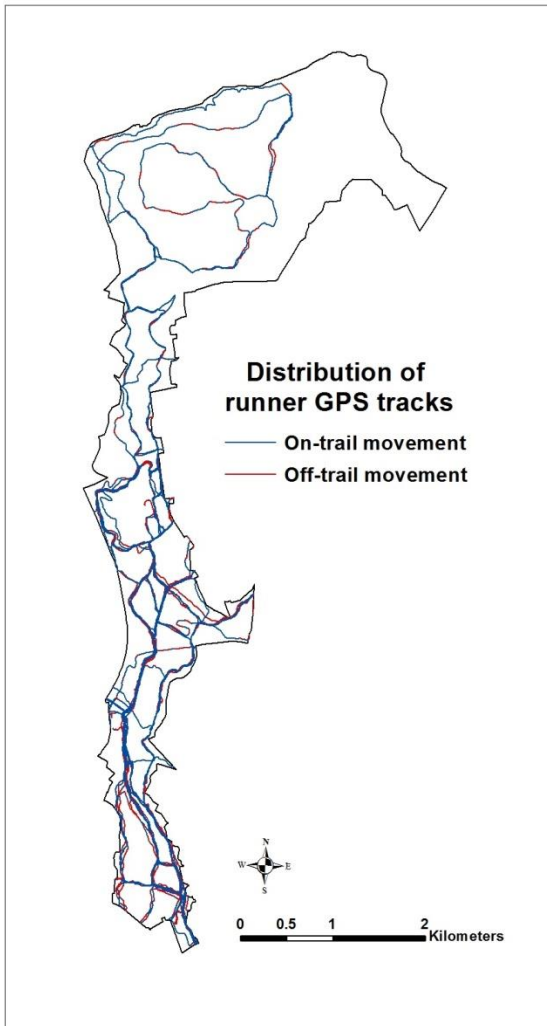


Fig. 2 Spatial distribution of runner GPS tracks (n=25)

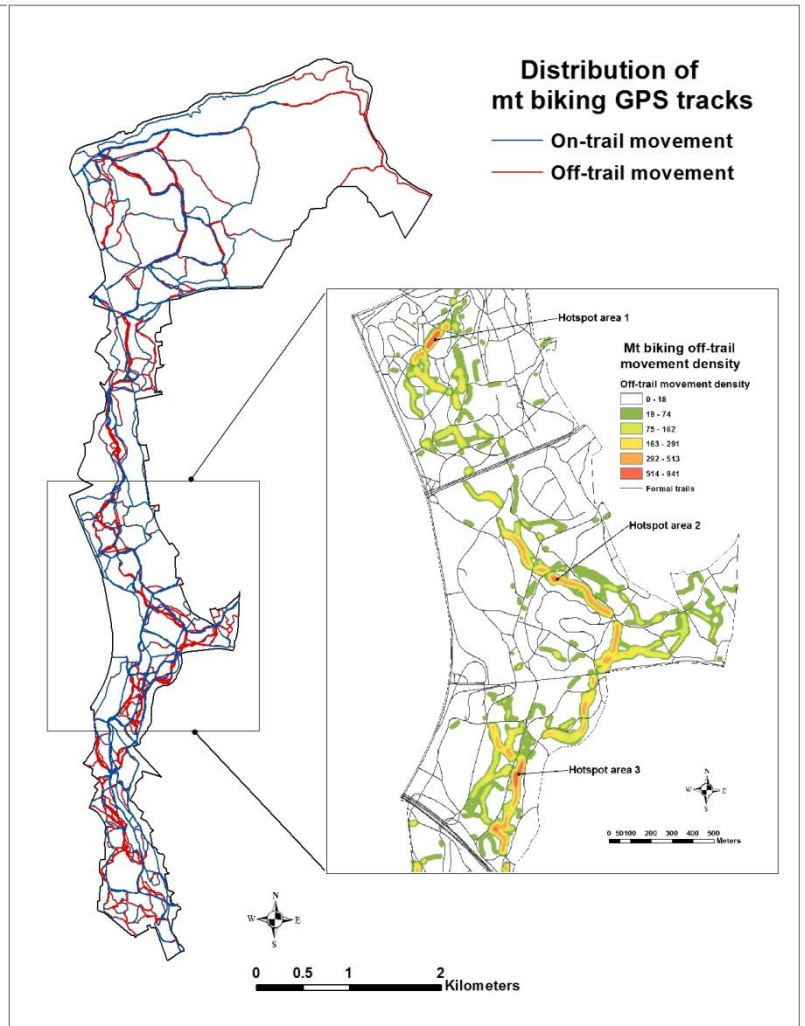


Fig. 3a Spatial distribution of mountain biker GPS tracks (n=22)

Fig. 3b Map of mountain bikers' off-trail movement density and location of hotspot areas sampled on the field

Fieldwork verification

Our fieldwork verification confirmed that the hotspot analysis identified accurately specific areas of high intensity of mountain biking off-trail use. The small-scale on-site mapping supported the hypothesis as all hotspots displayed higher level of vegetation wear than the coldspots (Fig.4).



Fig. 4 Examples of path and vegetation wear from sampled areas: A) heavily used and worn out off-trail path in sampled hotspot 2; B) sampled coldspot 2 with preserved vegetation and no visible paths; C) heavily used and worn out off-trail path in sampled hotspot 3; D) sampled coldspot 3 with generally preserved vegetation and two narrow paths with slightly reduced vegetation cover

Each hotspot sample plot included one main path up to 4.5 m wide with a maximum wear class of 4, meaning bare mineral soil or a deeply worn humus layer, and no vegetation on the paths (Table 1). Heavy wear was concentrated on the main paths, leaving forest floor vegetation in the rest of the hotspot plots better preserved. The coldspots in contrast displayed little or no visible effects of wear, with no paths or only a few narrow ones (0.2 – 1 m wide) inside the plot (Fig.5, 6 and7).

| Location | Size | Plot ID | Environmental characteristics of the sampling plot | Path characteristics (width, wear class) |
|-----------------------------------|---------|---------|---|---|
| Pirkkola (hotspot area 1) | 10 x 50 | HS1 | 40% rocky, semi-open pine dominated; 60% spruce dominated | 1 main path (1.6 - 2.6 m, class 4); 2 smaller paths (0.4 m, class 3; 0.5m, class 2) |
| | | CS1 | 15% rocky, semi-open pine dominated; 80% spruce dominated forest; 5 % boggy, wet area | 4 small paths (0.2 - 0.4 m, class 2) |
| Maunula North (hotspot area 2) | 20 x 25 | HS2 | 60% rocky, semi-open pine dominated; 40% spruce dominated | 1 main path (1.4 - 4.5 m, class 4); 1 small path (0.6 - 0.8 m, class 3) |
| | | CS2 | 20% rocky, semi-open pine dominated; 80% spruce dominated | no visible paths |
| Maunula South (hotspot area 3) | 15 x 20 | HS3 | 100% rocky, semi-open pine dominated | 1 main path (1 - 2.8 m, class 4) |
| | | CS3 | 95% rocky, semi-open pine dominated; 5 % boggy, wet area | 2 small paths (0.3 - 1 m, class 1-3) |

Table 1. Field samples of hotspot (HS)/coldspot (CS) recreational movement areas in Keskuspuisto. The wear classification is based on visual estimation: 0 = untrampled vegetation, no visible effects of wear; 1 = visible effects of wear, vegetation damaged, but only slightly reduced in cover; 2 = visible effects of wear, vegetation damaged and reduced in cover, but not completely worn away; 3 = generally no vegetation on the path, humus layer not worn away, rocks and tree roots sometimes uncovered; 4 = bare mineral soil or a deeply worn humus layer, no vegetation remaining, rocks and tree roots often uncovered (Lehvavirta, 1999).

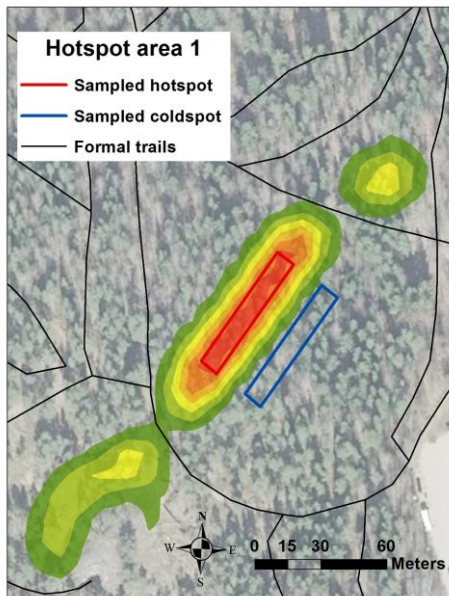
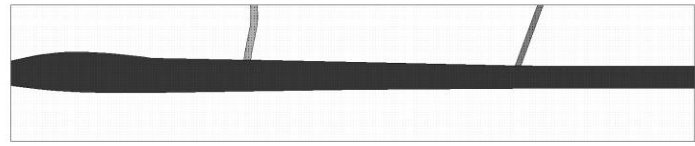
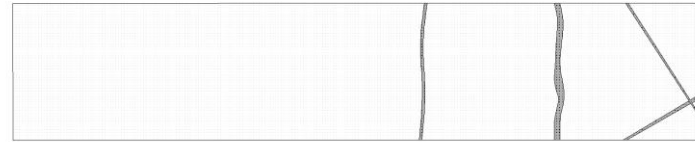


Fig. 5a Location of sampled hotspot/coldspot in hotspot area 1 (Keskuspuisto, Pirkkola)

Sampled hotspot 1



Sampled coldspot 1



0 5 10 20 Meters

Wear class



Fig. 5b Field maps of sampled hotspot (top) and coldspot (bottom) representing wear class (0-4, see explanations in Table 1) of paths and vegetation segments

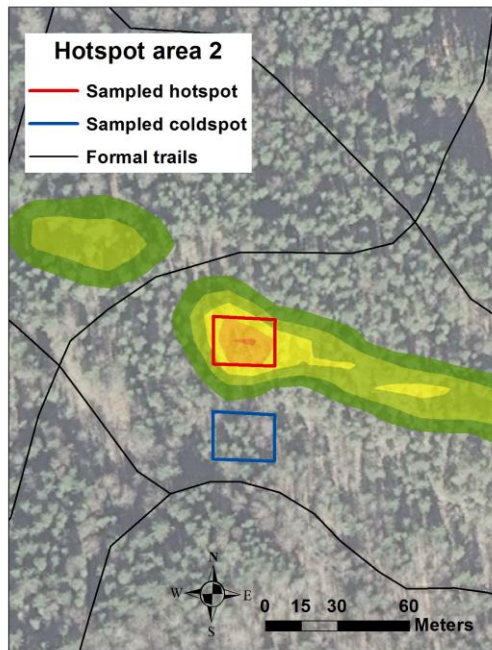


Fig. 6a Location of sampled hotspot/coldspot in hotspot area 2 (Keskuspuisto, Maunula North)

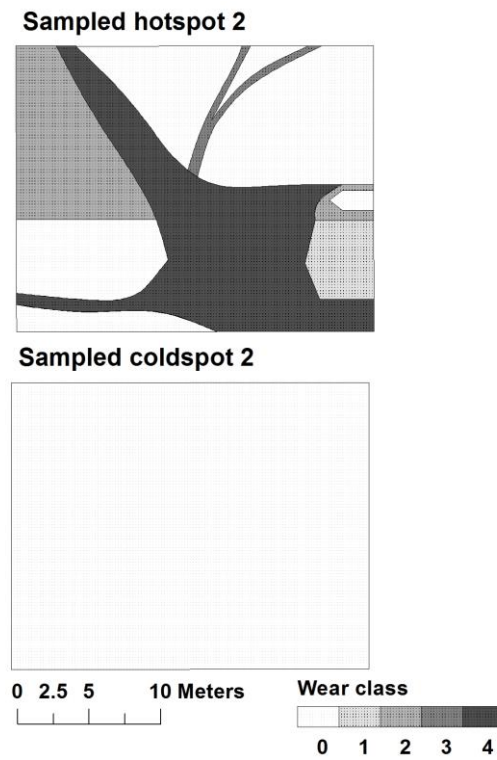


Fig. 6b Field maps of sampled hotspot (top) and coldspot (bottom) representing wear class (0-4) of paths and vegetation segments

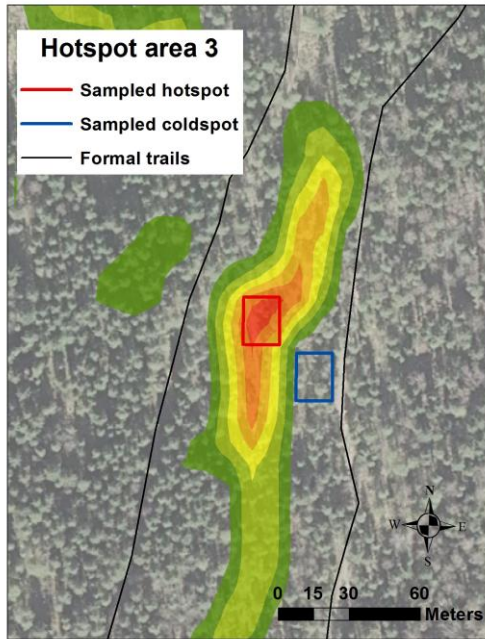


Fig. 7a Location of sampled hotspot/coldspot in hotspot area 3 (Keskuspuisto, Maunula South)

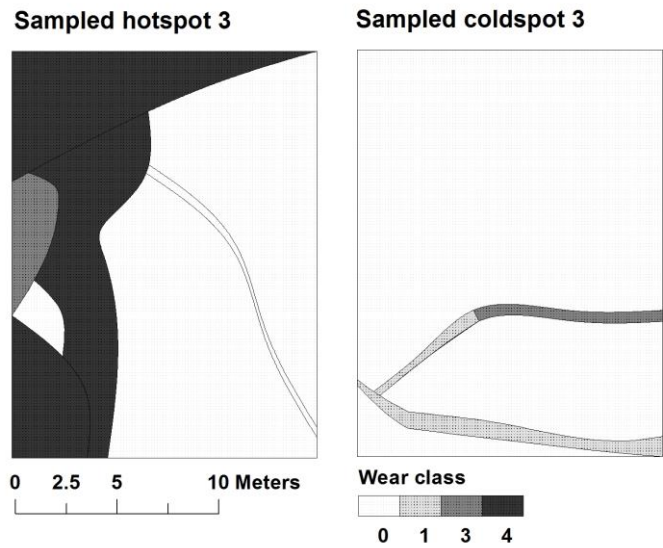


Fig. 7b Field maps of sampled hotspot (left) and coldspot (right) representing wear class (0-4) of paths and vegetation segments

4. Discussion

The pilot phase of this study illustrated the capacity of smartphone GPS tracking to collect accurate and detailed spatial information on recreational movement in multiple-use urban forests. The SGT method offers several methodological and practical benefits. First, it decreases the need for observational fieldwork by researchers or self-reported routes of participants that may be biased or less accurate (Arnberger & Haider, 2005; Hallo et al., 2012; Wolf et al., 2012). The data collection approach presented here is cost-effective, accessible and user-friendly as participants use their own smartphones and do not need to carry a GPS logger or download a specific software application. This significantly reduces investment costs, the potential loss of research equipment and the need for training for participation (Wolf et al., 2015). Research participants are simply being asked to share routes they have already collected, which has an intrinsic value of using available volunteered spatial information for new and undiscovered purposes, while potentially improving spatial enablement of citizens and the co-production of geographical knowledge (Feick & Roche, 2013). However, future research could investigate whether using familiar/personal equipment may lessen perceptions of being tracked and how the original motive for using the tracking application (e.g. private vs. social, self-tracking vs. research) may affect human spatial behaviour.

At the same time, there are significant challenges that revolve around the SGT method. Perhaps the most common concern relates to privacy issues associated with data gathered from personal mobile phones (Meijles et al., 2013; Taczanowska et al., 2008). For example, disclosing start and end points of a GPS track or displaying routine route of an individual can reveal a home or work location (Sainio et al., 2015). This study and others (e.g. Nitsche et al., 2014; Wolf et al., 2012) show that protection of participants' privacy can be maintained by guaranteeing anonymity, analysing only parts of the GPS tracks that fall within the

boundaries of the studied natural area, and by using the principle of informed consent i.e. providing volunteers with clear terms and conditions of participation. Nevertheless, to avoid negative consequences for human subjects such as sanctioning for off-trail use, we recommend that the SGT methodology is not used in protected areas where off-trail use is strictly forbidden.

A major constraint in this study was that we were not able to control the sample as regards different phone devices and sports tracking applications, different personal motivations, and various times of data generation. Noted for VGI studies in general, this heterogeneous nature of the data makes it particularly challenging to assess the data accuracy and consistency as quality and veracity may vary not only within the entire dataset, but also within the individual record collected by a singular user (e.g. due to GPS loss of signal) (Feick & Roche, 2013; Flanagan & Metzger, 2008).

In order to estimate location accuracy, here we measured the average deviation of on-trail GPS tracks (from participants who claimed to have followed formal trails) to the formal trail network. The results showed an average deviation of 9 m, which is in line with previous studies that have indicated a 5-10 m GPS positioning accuracy of smartphones (Hess et al., 2012; Menard, Miller, Nowak, & Norris, 2011; Zandbergen, 2009). However, there might be a level of uncertainty related to on-trail claims e.g. due to issues with participant recall of the visit (D'Antonio et al., 2010) or inability of recreational users to differentiate formal paths from informal trails while being outdoors (Wimpey & Marion, 2011). This could be particularly challenging in natural areas with varied and dense path networks such as Keskuspuisto. For example, Keskuspuisto has formal (signposted) nature-trails that consist of non-surfaced, narrow paths winding through the forest.

From a methodological perspective, detailed and accurate data on the formal network is essential in order to measure the GPS positioning accuracy and distinguish between on-trail and off-trail movement. In practice, official spatial datasets may often lack fully extensive data on formal trails (Hudson, Duthie, Yatinkumar, Larsen, & Meyer, 2012) and as found in this study, they could show inconsistencies in location accuracy, which makes it challenging to treat them as objective standpoints when high level of detail is needed. High resolution satellite images, combining different digital spatial datasets (e.g. from various public agencies or VGI datasets) and completing manually the formal trail network could provide maps with substantial level of detail and improve significantly future research (Hudson et al., 2012; Meijles et al., 2013).

Despite these limitations, the SGT methodology holds great potential for nature management applications. Perhaps the best advantage of the method lies in its ability to easily acquire timely spatial information about actual and changing movement in a variety of outdoor environments. The GPS data can be used to study differences in spatial patterns among user groups (e.g. Beeco, Hallo, & Brownlee, 2014; Meijles et al., 2013) as also demonstrated in this study with runners' and mountain bikers' use of formal trails and informal paths in Helsinki's Keskuspuisto. Our results indicated that runners mostly stayed on formal trails, while half of the mountain bikers' movement was off-trail, distributed along several major informal paths. This supports previous research that recreational use is often spatially concentrated in natural areas (Hadwen, Hill, & Pickering, 2007; Orellana et al., 2012; Walden-Schreiner & Leung, 2013) and although off-trail movement may be complex, it is often clustered along a few informal trails (as also shown by Walden-Schreiner and Leung (2013) findings in Yosemite National Park, USA). Although no error handling of the GPS data was conducted during the pilot phase (which is important for avoiding inaccuracies in the results), the hotspot fieldwork mapping served as 'real life verification'. Nevertheless, we

recommend that the hotspot analyses are locally validated as the level of wear and the spatial extent of impacts may vary depending on the context and environmental characteristics of the study site.

Only a small amount of GPS data was analysed in this explorative study. The results are not conclusive and may be biased due to overrepresentation of a specific user group (male, young, active, highly educated users). Further data collection is essential in order to increase representation of the user population and explore statistical differences between recreational groups in Keskuspuisto.

5. Conclusions

This research note demonstrates that smartphone GPS tracking can gather usable, low-cost and up-to-date information providing urban planners and managers with better understanding of the spatial distribution and intensity of recreational movement (Walden-Schreiner & Leung, 2013). SGT can help analyse and respond to trends in visitors and ecological impacts as they occur (Hadwen et al., 2007) pointing out where management practices need to be adapted before environmental conditions are too difficult to restore (Wolf et al., 2012).

SGT can help capture and visualise complex off-trail behaviour and map visitor-created paths that change quickly in time and space. This presents a valuable alternative to field surveys which could obtain accurate spatial data on informal paths but prove time-consuming, expensive and invalid over time (Walden-Schreiner & Leung, 2013). In the example we presented with mountain biking in Keskuspuisto, the hotspot analysis accurately and effectively located spatial clustering of off-trail movement in intensively used areas where widening of paths and heavy wear could be observed. Management in such parts of the forest may need to be adapted and could target e.g. guiding recreational users away from sensitive vegetation (Chiou, Tsai, & Leung, 2010) or using preventive interventions at locations where

recreational disturbance has started to increase (Hauru et al., 2012; Lehvavirta, 1999; Marzano & Dandy, 2012).

However, in order to effectively manage and guide recreational use while allowing for high-quality and inspiring nature experiences of visitors, knowledge of movement patterns alone may not be sufficient and route choice motives should also be deeply understood. To make the SGT method even more fruitful, further research work could link GPS tracking data with questionnaires to gain better knowledge of the socio-cultural background of visitors and environmental features that may influence their spatial behaviour inside the urban forest. We hope that by presenting results at an early stage, this paper can provide a foundation for researchers to continue to develop and improve the SGT methodology for use in various natural resource applications. Urban forests here serve as a case of a larger phenomenon of the interplay of recreational behaviour and green infrastructure. Methods and results concerning them could inform the management of recreational areas globally.

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List of tables

Table 1. Field samples of hotspot (HS)/coldspot (CS) recreational movement areas in Keskuspuisto. The wear classification is based on visual estimation: 0 = untrampled vegetation, no visible effects of wear; 1 = visible effects of wear, vegetation damaged, but only slightly reduced in cover; 2 = visible effects of wear, vegetation damaged and reduced in cover, but not completely worn away; 3 = generally no vegetation on the path, humus layer not worn away, rocks and tree roots sometimes uncovered; 4 = bare mineral soil or a deeply worn humus layer, no vegetation remaining, rocks and tree roots often uncovered (Lehvävirta, 1999).

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Fig. 1 A segment of typical GPS tracks and the 10 m formal trail buffer. Formal trail network available from National Land Survey of Finland.

Fig. 2 Spatial distribution of runner GPS tracks (n=25)

Fig. 3a Spatial distribution of mountain biker GPS tracks (n=22)

Fig. 3b Map of mountain bikers' off-trail movement density and location of hotspot areas sampled on the field

Fig. 4 Examples of path and vegetation wear from sampled areas: A) heavily used and worn out off-trail path in sampled hotspot 2; B) sampled coldspot 2 with preserved vegetation and no visible paths; C) heavily used and worn out off-trail path in sampled hotspot 3; D) sampled coldspot 3 with generally preserved vegetation and two narrow paths with slightly reduced vegetation cover

Fig. 5a Location of sampled hotspot/coldspot in hotspot area 1 (Keskuspuisto, Pirkkola)

Fig. 5b Field maps of sampled hotspot (top) and coldspot (bottom) representing wear class (0-4, see explanations in Table 1) of paths and vegetation segments

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Fig. 7a Location of sampled hotspot/coldspot in hotspot area 3 (Keskuspuisto, Maunula South)

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