Applied Geography 150 (2023) 102825

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Evaluation of GNSS-based Volunteered Geographic Information for assessing visitor spatial distribution within protected areas: A case study of the Bavarian Forest National Park, Germany

Laura Horst [a], Karolina Taczanowska [a,*], Florian Porst [b], Arne Arnberger [a]

[a] Institute of Landscape Development, Recreation and Conservation Planning, Department of Landscape, Spatial and Infrastructure Sciences, University of Natural Resources and Life Sciences Vienna, Peter-Jordan-Strasse 82, 1190, Vienna, Austria

[b] Bavarian Forest National Park, Freyunger Straße 2, 94481, Grafenau, Germany

A R T I C L E I N F O

Keywords:
GNSS
GPS
VGI
Social media
Protected area
Recreation
Tourism
Visitor monitoring
Bavarian Forest National Park
Hiking
Recreational trails
GPS tracking
Big data
GPSies
Outdooractive
Komoot
Nature protection
Visitor management
Spatial behaviour

A B S T R A C T

Systematic monitoring of recreational use in vulnerable ecosystems is crucial to balance human needs and site capacities. Recently, publicly available digital data, including Global Navigation Satellite System-based Volunteered Geographic Information, gained attention as a potential resource depicting visitor movement. However, there is a need to critically assess its reliability for visitor monitoring across countries, regions and available databases. Our research evaluates the usability of GNSS-based VGI-data obtained from three common platforms: GPSies, Outdooractive, and Komoot for assessing the spatial distribution of hikers in the Bavarian Forest National Park. A total sample of 1742 GNSS-tracks uploaded between 2013 and 2018 were compared across data platforms. Additionally, available systematic field counts, carried out between 2013 and 2014 (11 Eco-Counter sensors), were compared to GNSS-based VGI data uploaded within the corresponding period. The comparisons at individual and collective levels (route lengths, kernel density, optimized hotspot analysis along with fishnet-based counts of GNSS-tracks) showed similarities between VGI data platforms. Data obtained from GPSies and Outdooractive displayed a higher correlation with each other than with those obtained from Komoot. Also, for GPSies, there was a significant positive correlation between VGI-data and field count data. Data sample of Outdooractive and Komoot within the specified spatio-temporal frame was too small to compare with available field count data. We highlight the necessity of systematic validation of GNSS-based VGI data resources, being complementary rather than the primary data source in visitor monitoring and recreation planning. Also, systematic long-term visitor monitoring using other methods is crucial to assess the validity of novel data resources, such as GNSS-based VGI.

1. Introduction

1.1. Visitor monitoring techniques and VGI

Managing recreational activities in protected areas (PA) belongs amongst the major challenges in popular tourism destinations (Bell et al., 2007; Buckley, 2003; Burns et al., 2010; IUCN, 2018). Therefore, reliable data describing human recreational behavior, along with efficient reliable data collection methods are needed to support successful management of those environmentally sensitive leisure sites (Cessford & Muhar, 2003; Gutzwiller et al., 2017; Taczanowska et al., 2008). Systematic visitor monitoring in protected areas has a long tradition within the international context and covers various aspects of recreational use (Cessford & Muhar, 2003; Hadwen et al., 2007; Pickering et al., 2018) including monitoring visitation numbers, activity types, movement patterns and socio-demographic visitor characteristics (Bielański et al., 2018; Buckley, 2003; Cessford & Muhar, 2003; Hennig, 2007; Levin et al., 2017). Numerous methods have already been used for this purpose, comprising: direct and indirect observation, automatic counting devices, visitor tracking, counting of access permits and tickets, interviews, self-registration, internet-based user-generated content, traces of use (Bielański et al., 2018; Muhar et al., 2005). Each technique has specific advantages and limitations; therefore a simultaneous combination of data collection methods is frequently being applied to capture

Abbreviations: GNSS, Global Navigation Satellite System; VGI, Volunteered Geographic Information.

* Corresponding author.
E-mail addresses: karolina.taczanowska@boku.ac.at, karolina.taczanowska@boku.ac.at (K. Taczanowska).

https://doi.org/10.1016/j.apgeog.2022.102825
Received 8 January 2022; Received in revised form 10 October 2022; Accepted 19 November 2022
Available online 25 November 2022

comprehensive characteristics of recreational use (Bielański et al., 2018; Heikinheimo et al., 2017; Korpilo et al., 2017).

Technological advances and the growing use of location-based services (LBS) are opening up new opportunities for collecting georeferenced information about visitor behavior in protected areas (Campelo & Nogueira Mendes, 2016; Di Minin et al., 2015; Heikinheimo et al., 2017, 2020). Examples of LBS within outdoor recreation domain include fitness and/or touring online platforms such as Outdooractive, Komoot, Strava, Adidas Runtastic, or GPSies. Those services also allow networking among LBS-user communities, and the sharing of tours, reviews, and photos related to recreational activities, such as hiking, jogging, cycling, cross-country skiing, and mountain biking. (GPSies, 2019; Komoot, 2019; Korpilo et al., 2017; Outdooractive, 2019a; Runtastic, 2020; Strava, 2020). Users of these services utilize their smartphones or other GNSS-equipped devices to record and upload their tours (Campelo & Nogueira Mendes, 2016; Heikinheimo et al., 2017). The data, referred to as Volunteered Geographic Information (VGI) (Goodchild, 2007), has been increasingly used as an additional data source for visitor monitoring in protected areas over the past decade (Campelo & Nogueira Mendes, 2016; Korpilo et al., 2017; Norman et al., 2019; See et al., 2016).

Recent studies highlight the advantages of VGI compared to other survey methods, especially in respect to its low data collection effort (Campelo & Nogueira Mendes, 2016; Korpilo et al., 2017). The ability to acquire large sets of digital data makes it attractive for visitor monitoring (Heikinheimo et al., 2017). Moreover, unlike costly on-site survey and counting methods, these data are already widely available for many parts of the world, and their distribution will continue to increase with the ever-growing availability of smartphones (Campelo & Nogueira Mendes, 2016; Di Minin et al., 2015). Notably GNSS-based VGI data may deliver valuable information on the spatio-temporal distribution of visitors within recreational destinations. GNSS-based VGI data is available online as a GNSS-track (GPX file) that contains movement trajectories of visitors sharing their routes with an online community. This allows people to identify high or low use trails in a protected area and when the trails are used. In contrast to automatic counting devices, the entire route and, if specified by the user, activity en route can be recorded (Norman et al., 2019). Passive data collection also allows for better monitoring of unauthorized visitor activity than an active collection method, where the visitors may adjust their behavior due to the presence of human observers (Arnberger et al., 2005; Cessford & Muhar, 2003; Heikinheimo et al., 2017; Norman et al., 2019). However, GNSS-based VGI data do not deliver exact information on visitor numbers at a certain point and time period in contrast to visitor counters.

It should be kept in mind that users of any platform represent only a sub-population of the visitor community that may be a sub-culture and not merely a representative sample of the whole community, so possible biases need to be acknowledged and investigated (Di Minin et al., 2015; Ruths & Pfeffer, 2014). Since information on age, gender and socio-economic status is either not publicly available on the platforms or is anonymous, statements on demographics can only be made through representative quantitative surveys. A study conducted in the USA in 2015 on the use of mobile health and fitness apps found that the users of such platforms are primarily younger, earn a comparatively higher income and usually have a higher level of education (Krebs & Duncan, 2015). It can be assumed that the expression of the demographic bias depends not only on the particular platform used, but also on the type of recreation area, the activity, and the origin of the visitors (urban, rural, nationality, culture) (Fisher et al., 2018). It therefore makes sense to compare the data with other survey methods, such as automated counts or systematic route surveys. Furthermore, the use of the crowdsourced data must always be considered from a legal and ethical perspective. A user uploading content does not automatically imply an agreement to the data being used for research purposes (Salganik, 2018; Toivonen et al., 2019; Zook et al., 2017). In any case care over use of sensitive data must be taken by researchers.

Data representativeness problem of GNSS-tracking data might be reduced in field tracking studies, where GNSS/GPS loggers are distributed among randomly selected visitors on the pre-defined sampling days. This method is well-established in recreation research domain (Bielański et al., 2018; D'Antonio & Monz, 2016; Sykes et al., 2020; Taczanowska et al., 2014) yet it requires more organisational and technical effort in comparison to downloading GNSS-based VGI data.

A recent alternative to actively collected and shared GNSS-based VGI data is the use of passively acquired mobile device location data, offered by commercial providers (e.g. telecommunications service providers). Anonymized mobile device location data were successfully used to monitor visitor behavior in several North American recreational areas (Creany et al., 2021; Monz et al., 2019, 2021).

1.2. Spatial use patterns of protected area visitors

One of the basic movement parameters, characterizing the spatial distribution of visitors in protected areas is the length of individual tours, since it provides information about potential activity range and penetration of a recreational area. In general, the tour length increases with the length of stay, but day hikers often take more breaks during longer stays (Taczanowska et al., 2008). Hikers also tend to choose half-day tours that are more than 5 km but less than 50 km long (Hennig & Groβmann, 2008). An on-site visitor survey in the Bavarian Forest National Park showed that the average tour length of hikers is about 7 km. Locals chose shorter routes, while tourists took longer ones (Arnberger et al., 2015). Arnberger and Hinterberger (2003) found in an on-site survey in a peri-urban national park that tour length and spatial behavior varied by activity. The tours of bicyclists were the longest ones with about 10 km on average, followed by joggers (8.2 km), dog walkers (6.1 km) and walkers (5.8 km) (Arnberger & Hinterberger, 2003). They further found that dog walker use was concentrated on trails nearby residential areas. Norman et al. (2019) used VGI on MapMyFitness (Under Armour, 2021) to investigate, among other things, the length of hiking tours for three protected areas in Australia which were an average of 8.2 km (Norman et al., 2019). Campelo and Nogueira Mendes (2016) and Jurado Rota et al. (2019) used VGI to capture the spatial behavior of bicyclists in protected areas and found that it can be helpful information for monitoring and managing recreational areas.

Next to parameters describing individual movement trajectories, analysis at a collective level are of high importance from the spatial planning and recreation management perspectives (Jiang et al., 2021; Skov-Peterson & Gimblett, 2008). Analysis of a collective spatial behavior informs where and when the visitors actually go and which parts of a recreational area are being used (Cessford & Muhar, 2003; Skov-Peterson & Gimblett, 2008). Collective spatial behavior patterns of various recreational activity groups or specific visitor profiles are important subjects of investigation (Byczek et al., 2018; Švajda et al., 2018). Spaces suffering from overuse and potential locations of social or ecological conflicts may be determined, based on collective visitors' traces (Byczek et al., 2018; Rupf et al., 2011; Wolf et al., 2018). Moreover, spatio-temporal aspects, such as investigating changes in visitor distribution at different temporal resolutions (e.g. different times of the day, week and the year) belong to frequently studied issues in recreation research (Kim et al., 2019). Fine-resolution GNSS-tracking data allow us to investigate off-trail behavior in restricted areas (Bielański et al., 2018; Kidd et al., 2015).

1.3. Validation of VGI data

Although many authors highlight the utility of GNSS-based VGI for visitor monitoring, only a small selection of studies recognize the importance of the validation of these crowdsourced data. Recently, examples of data validation: comparing GNSS-based VGI data across various platforms (Campelo & Nogueira Mendes, 2016; Heikinheimo et al., 2020; Norman, Pickering 2017); GNSS-based VGI data with field counting (Norman et al., 2019; Norman & Pickering, 2017); and visitor survey data (Heikinheimo et al., 2020) have been carried out. Campelo and Nogueira Mendes (2016) suggested that the validity of GNSS-based VGI data could be tested with counting devices. Norman and Pickering (2017) matched counter data in the form of the average amount of passage per month and VGI from MapMyFitness (Under Armour, 2021), procured between December 2016 and February 2017, for seven trails in one of their three study areas. They showed a strong relationship between them. Here, the online data are primarily seen as a supporting instance type to the existing monitoring data and a comparison with these is suggested in order to investigate their representativeness (Norman & Pickering, 2017). Fisher et al. (2018) examined user-generated social media content, i.e., georeferenced photos from Flickr from 2005 to 2015 and tours from an online hiking guide posted during 2016 and compared these with data from counting devices from late August 2016 through December 2016. For the 15 trail areas observed in a National Forest in Washington, they found a strong correlation of the data sets in terms of their spatial distribution, and thus highlighted the potential of user-based data, in combination with other quantitative survey methods, to represent spatial visitor behavior (Fisher et al., 2018). Norman et al. (2019) took a similar approach. For their study, the relative monthly popularity of a trail, determined by count data, was compared to the number of online trips. It was found that the relative popularity of places, based on counter data and online data, were similar, specifically, online jogging tours were mostly highly correlated with count data (Norman et al., 2019). These validation studies only partly considered the overall spatial distribution of recreational uses in an area. Some authors use qualitative, visual comparisons of density maps, based on GNSS-based VGI data (Norman et al., 2019; Norman & Pickering, 2017), while the others perform quantitative comparisons of individual raster cells within a study area, where the number of visitors' digital traces grouped by data source is being calculated (Campelo & Nogueira Mendes, 2016; Heikinheimo et al., 2020).

1.4. Study objectives

As previous studies reported differences in use across different GNSS-based VGI platforms and world regions, we aim to complement the ongoing discussion on the reliability of GNSS-based VGI data for visitor monitoring. We focus our research on a popular European protected area, the Bavarian Forest National Park, because of the availability of different GNSS-based VGI and visitor count data.

We aim to investigate the spatial distribution of hikers, based on data obtained from three different GNSS-based VGI platforms, eventually comparing results grouped by data source and correlating them with visitor numbers collected by automatic visitor counters.

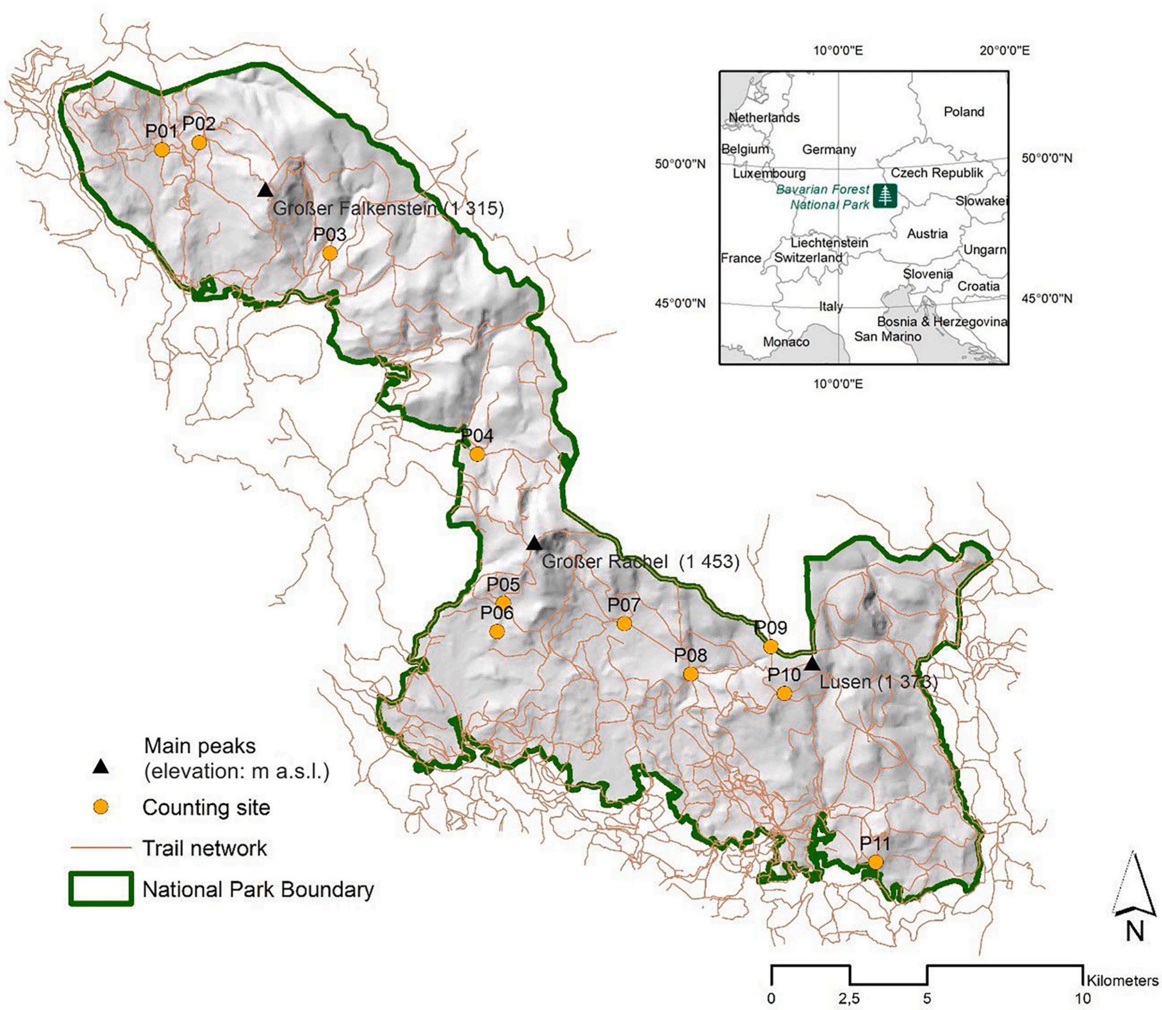

Fig. 1. Study area: Hillshade model of the Bavarian Forest National Park with trail network, the location of visitor counting sites and the three highest summits (Geodata source: arcgis.com 2020, bkg.bund.de 2020, NLPVW BW 2014, NLPVW BW 2019, opendata.bayern.de 2019).

2. Materials and methods

2.1. Study area

The Bavarian Forest National Park (German: *Nationalpark Bayerischer Wald*) is located in Europe, southeastern Germany in the federal state of Bavaria and borders the Czech Republic on its eastern side. The 24 250 ha large protected area is assigned to the IUCN category II (Bundesamt für Naturschutz, 2020; Job et al., 2019; Nationale Naturlandschaften, 2020; Nationalparkverwaltung Bayerischer Wald, 2014). The tourist infrastructure of the Bavarian Forest National Park and the region can be used both in summer and winter as a network of trails with about 350 km of hiking trails, 200 km of cycling trails and 80 km of cross-country ski trails runs through the National Park area. Hikers can use all marked trails in compliance with the trail regulations (Nationalparkverwaltung Bayerischer Wald, 2014). The National Park counts almost 1.4 million visits annually (Porst et al., 2020, p. 71). Fig. 1 illustrates the location of the Bavarian Forest National Park including a network of recreational trails.

2.2. Data resources

The platforms GPSies, Outdooractive and Komoot were considered as data sources GPSies, 2019; Komoot, 2019; Outdooractive, 2019a). After an inspection from 2016 to 2018 of various platforms by the National Park administration, those three platforms were selected for closer analysis due to their high or growing number of tracks for the Bavarian Forest National Park in comparison to other services. The automated download of GNSS-based VGI data was carried out. The automated recording is a browser-based application that records all hiking tours that have been uploaded for the area of the Park for a specified period of time. The possibility of multiple use of this application allows regular updating of the database, so that recently uploaded tours are also available. The decisive factor in the selection of tours was the upload date in order to avoid duplications. Next to GNSS-tracks, additional publicly available information associated with the tours, such as the name of the tour, type of recreational activity, date of creation, length of tour, number of views and downloads, were acquired. Komoot contains so-called ‘smart tours’ which are generated based on user-defined highlights with the help of an algorithm (Komoot 2020a, 2020c). There are also community tours created as user-generated content by the members of the platform. These tours only become visible when Komoot “adventurers” or “explorers”, as members are known, visit or follow the tour creator’s member profile (Komoot, 2020b; 2020c). Since only the last form is VGI, only these community tours were used for the evaluation. GPSies has become part of AllTrails, but is listed under its old name in this study, as we investigate time period before 2019 (AllTrails, 2019). Table 1 summarizes main characteristics of the investigated tour platforms.

The downloaded GPX files were converted into point shapefiles and a projection of the layers into the UTM (Universal Transverse Mercator) reference system was performed. Due to the use of a broader bounding box in the automated collection of data from GPSies and Komoot, there were tours located outside of the National Park area in the initial database. However, by intersecting the data with the National Park area, only tours located within the Bavarian Forest National Park boundary were considered in the study. Especially for the GPSies, this led to a strong reduction of the data set, since most of the automatically downloaded tours did not pass through the National Park. The Outdooractive tours, on the other hand, all crossed the protected area. Furthermore, only data uploaded between January 1, 2013 and December 31, 2018 were included in further analyses for comparability between the platforms. All tours with the activity ‘hiking’ were selected, as this is the most frequently practiced recreational activity in the Bavarian Forest National Park (Porst et al., 2020, p. 71). In the selected database of the platforms, there were still tours that were subject to sources of error in the recording. The removal of these data was based on visual inspections. Table 2 gives an overview of the entire data selection process, ranging from the initial download of GNSS-based VGI data within a specified bounding box up to final data set used for further analysis. In total, 402 relevant data records were available for GPSies, 250 tours were available for Outdooractive, and 1090 tours were available for Komoot.

For the evaluation of the GNSS-based VGI data, automatic counter data (pyro sensors, Eco-Counter) which had collected visitor data at eleven sites between 2013 and 2014, were used (Fig. 1). Only entries to the Bavarian Forest National Park were considered, as entries were used for the calculation of the total number of visitors to the National Park within one year. The counter values were corrected by a calibration factor (Arnberger et al., 2015). The total number of entries from April 28, 2013 to April 27, 2014 recorded by all eleven counters was 250 552 and ranged from about 5300 to 79 000 entries per site (Arnberger et al., 2015). A subset of GNSS-based VGI data uploaded between April 28, 2013 and April 27, 2014 was used to compare field counts and VGI data.

2.3. Data analysis

First, tour lengths of the Park were compared between three VGI platforms. For this purpose, the GNSS-track points were converted into tracks (line features classes) within a geodatabase in ArcGIS. Each track was assigned a unique ID and length attribute. Descriptive statistics was used to characterize trip lengths grouped by VGI platform.

In order to analyze a collective spatial distribution of visitors in the study area, three various spatial analysis methods were applied: 1) kernel density analysis; 2) hotspot analysis and 3) tracks count per raster cell (fishnet counts). The following figure (Fig. 2) illustrates a detailed

Table 1
Comparison of the three platforms
(Summary based on: AllTrails, 2022, Outdooractive, 2022, Koomot, 2022, Hallermann, 2019; Holzmüller, 2011).

	GPSies/ AllTrails*	Outdooractive	Komoot
Established	*2006*	*2008*	*2010*
Registered users worldwide	*~40 million*	*~13 million*	*> 27 million*
Main user groups	*Hikers, Bikemap, Runners*	*Hikers, Bikers, Mountaineers*	*Hikers, Bikers, Runners*
Available tour-information	*Type of activity* *Date of creation* *Length of the tour* *Number of views* *Number of downloads*	*Type of activity* *Date of creation* *Length of the tour* *Number of views* *Number of downloads*	*Type of activity* *Date of creation* *Length of the tour*

*) in 2019 GPSies was acquired by AllTrails.

Table 2
Overview of data selection process: 1) Data available within specified bounding box; 2) Intersection with the Bavarian Forest NP area; 3) Selection of tours uploaded within the study period (2013–2018); 4) Selection of the target activity type (hiking) and removal of invalid GNSS-tracks.

VGI platform	Number of downloaded tours available for the specified bounding box	Number of tours crossing Bavarian Forest NP area	Number of tours uploaded within the study period	Number of tours with assigned activity type “hiking” & valid GNSS-track (final dataset)
GPSies	*10 867*	*1292*	*849*	*402*
Outdooractive	*560*	*511*	*366*	*250*
Komoot	*3694*	*2599*	*1549*	*1090*
Total sum	*15 121*	*4402*	*2764*	*1742*

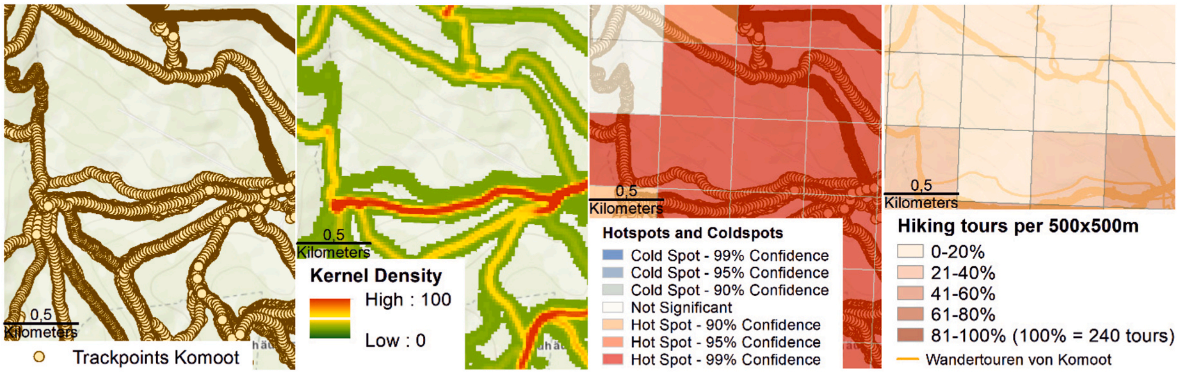

Fig. 2. Illustration of the applied methods for the same area in the Bavarian Forest National Park from left to right: a) input data (GNSS-trackpoints obtained from VGI-platform Komoot); b) kernel density; c) hotspot analysis; d) fishnet counts of hiking tours (Geodata source - GNSS-trackpoints: komoot.com 2019; basemap: OpenStreetMap 2021).

example of input data (GNSS-track points) and applied analysis (kernel density, hotspot analysis, and fishnet counts).

The kernel density analysis describes the density of objects in the neighborhood of these objects. The neighborhood corresponds to a previously defined circular search radius (ESRI, 2016b). A pre-defined search radius of 50 m was chosen in order to compromise GNSS-data accuracy and density of the trails network in the study area.

The ArcGIS optimized hotspot analysis procedure was used to determine the spatial distribution of visitors within the Park. In this approach, statistically significant spatial clusters were formed from the total number of trackpoints of a given data platform, which generated: hotspots, at high values; and coldspots, at low values, in several gradations. The gradation of the hotspots for each cell results from the strength of the significance and is here 99%, 95% or 90%. All values below this are classified as 'not significant'. The coldspots are graded in the same way, resulting in seven different cell types. This is done within a grid in which the individual cells are 500 × 500 m in size (ESRI, 2018a). The grid 500 x 500 was chosen after consultation with the National Park and was motivated by management implications.

In order to statistically compare the spatial distribution of tours across various VGI platforms, the study area was divided into homogenous spatial units, using a fishnet function. Initially, several grid sizes were considered for this analysis (1000 × 1000 m; 500 × 500 m and 250 × 250 m). In case of 1000 x 1000-m fishnet, correlations were higher, however the spatial resolution of the results was too general from the management perspective. 250 × 250 m resolution resulted in a high number of grid cells without tracks, or grid cells with very low values. Thus, as a trade-off between grid resolution, amount of visitor tracks and management perspective we decided for 500 × 500 m grid for final analysis. Square units were assigned unique IDs. Subsequently, the fishnet layer was intersected with GNSS-tracks. As a result, a fishnet layer, where each square contained a unique ID and the number of tracks passing through it, was calculated. The same fishnet reference layer was intersected with GNSS-tracks of each VGI-platform, resulting in a dataset containing the following attributes: 1) square ID; 2) number of GPSies-tracks; 3) number of Outdooractive tracks and 4) number of Komoot tracks. To assure better comparability between the three platforms, the values of track number per square unit were standardized to a range between 0 and 100% (where 100% indicated a maximum registered value in a given dataset and 0% indicated a square unit without any tracks). In this way, the dataset consisting of 1159 individual square units containing tour numbers originating from GPSies, Outdooractive and Komoot platforms were statistically comparable.

In order to establish a relationship between the number of GNSS-based VGI tours and the count data, a buffer of 50 m around each Eco-Counter sensor was applied to assign number of GNSS-tracks passing through this location. Spearman correlation was used to test whether there is a correlation between the number of counts at the eleven counting locations and the number of GNSS-tracks passing through those locations.

The analysis was carried out for three VGI platforms separately. The available field count data (acquired in the period between April 28, 2013 and April 27, 2014) were correlated with VGI data uploaded in the corresponding time period. Statistical analysis was done in SPSS. Spatial analysis was done in ArcGIS.

3. Results

3.1. Tour length

The average tour length across all platforms was 11.16 km and differed significantly between the platforms (Kruskal Wallis test: $H = 27.401$, $p < .001$). No differences between GPSies and Outdooractive were found, whereas Komoot tours were shorter (Table 3). The high standard deviations of GPSies and Outdooractive tours indicated a greater variation in tour length compared to Komoot. GPSies and Outdooractive, had a higher maximum tour length.

3.2. Kernel density of the hiking tours

The kernel density analysis revealed those areas within the Park that have a high density of trackpoints. The network of trails around the three highest peaks of the Park was found to be highly frequented on all three platforms. Only at the border crossing to the Czech Republic, at the northeastern end of the National Park, did the platforms show differences. Outdooractive and Komoot in particular recorded a high density of tours there, whereas GPSies did not provide any trends in this regard (Fig. 3).

3.3. Hot- and coldspots of the hiking tours

The hotspot analyses of the three platforms illustrated similar findings. Here, too, relevant hotspots were found for the areas around the peaks, which can be attributed to a high tour density. Likewise, Outdooractive and Komoot showed hotspots at the border crossing to the Czech Republic in the Northeast, which is only classified as an insignificant area by GPSies. Komoot is frequently used in the Czech Republic, which is probably why the number of cross-border tours is greater here (Fig. 4).

3.4. Spatial distribution of VGI tours within homogenous grid units (fishnet)

Using a 500 × 500m fishnet grid, the spatial comparison of the

Table 3
Descriptive statistics of the tour lengths of the three platforms.

	Number of tours	*Mean value (km)*	*Median (km)*	*Standard deviation (km)*	*Minimum (km)*	*Maximum (km)*
GPSies	*402*	*13.65*	*11.53*	*10.98*	*0.002*	*66.00*
Outdooractive	*250*	*12.90*	*11.30*	*10.67*	*0.03*	*66.15*
Komoot	*1090*	*9.84*	*9.78*	*5.35*	*0.02*	*39.54*

hiking tours showed squares inside the Park for which the number of hiking tours is high or low according to the respective platform. This corresponds to the previously mentioned results of the kernel density and hotspot analysis. What is striking about Komoot is the comparatively small number of squares with a recognizably higher number of tours. Despite the overall high number of tours for this platform, they seemed to be rather evenly spatially distributed (Fig. 5). The results of the Spearman correlation showed that the number of hiking tours passing through a certain square (500 × 500 m) of the Park area was strongly positively correlated with each other for all three platforms (Table 4). The strongest correlation of the spatial distribution of hiking tours could be found between GPSies and Outdooractive ($r = 0.928$, $p < .001$), as well as between Outdooractive and Komoot ($r = 0.845$, $p < .001$). For GPSies and Komoot, the correlation parameter is similar ($r = 0.817$, $p < .001$).

3.5. The comparison of VGI tours and count data

Thanks to availability of 1-year field visitor monitoring data at 11 National Park locations we intended to compare field count data with VGI data, downloaded within the corresponding time period (April 28, 2013–April 27, 2014). Table 5 presents correlation results. Significant positive correlation between field counts and number of tours obtained from GPSies for 11 specified locations was found ($r = 0.633$, $p = .037$). Due to a limited amount of VGI-data during the specified 1-year period, calculation of correlation between count data and Komoot data was not possible. Correlation between count data and Outdooractive data was not significant. However, at this point we would like highlight the problem of limited sample of VGI data that would exactly correspond with the period of visitor monitoring in the field. Due to missing long-term field counts at studied 11 National Park locations, no correlation between count data and VGI data for the 6-year-period (2013–2018) was calculated. We extensively report on this issue further in the discussion section (Section 4.3).

Within the period of 6-years (2013–2018) further comparisons across VGI-platforms (without considering field counts) at 11 mentioned National Park locations were possible. There were significant positive correlations between the numbers of tours obtained from different VGI-platforms. The correlation between GPSies and Outdooractive ($r = 0.902$, $p < .001$) as well as between GPSies and Komoot ($r = 0.779$, $p < .01$) were stronger than the correlation between Komoot and Outdooractive ($r = 0.637$, $p < .05$).

4. Discussion

4.1. Significance of the findings

The results suggest that GNSS-based VGI offers some new perspectives for visitor monitoring in protected areas. Notably, two of the investigated online platforms: “GPSies” and “Outdooractive” corresponded very well to each other, both in the spatial distribution of the recorded tours and lengths of hiking tours. Moreover, data obtained from these platforms showed a significant correlation with the count data, collected in the field. Furthermore, the results of kernel density and grid analysis correspond well with the spatial use data of a previous survey in the National Park (Allex et al., 2016).

These findings apply to the Bavarian Forest National Park but may differ due to different popularity of the platforms in other protected areas. It should also be noted that GNSS-based VGI data cannot simply replace a visitor census. On the one hand, the representation of aggregated spatial visitor distribution, based on GNSS-based VGI data collected over several years, seems possible, on the other one such data is not sufficient to depict more detailed spatio-temporal resolutions (e.g. comparisons in visitor distribution over seasons, course of the year or weekly and daily dynamics of recreational use).

In order to exploit further resources of VGI, the evaluation should be extended to the temporal aspect of visitor behavior, whereby the effect of management measures, such as the closure of a path, the construction of a new theme path or the establishment of an attraction point, could be recorded. In addition, the speed of movement, along with the starting and end points of the trips could be investigated in the future (Bielański et al., 2018). Off-trail behavior, of which visitors are usually unaware, can also be investigated with little effort using tours from online platforms (Bielański et al., 2018; Norman et al., 2019). At the same time, recording specific trail segments, where visitors violate park regulations provides the opportunity to take targeted visitor management actions online and in the field.

This work shows that GNSS-based VGI data can provide detailed and comprehensive information on spatial visitor behavior in protected areas. It demonstrates that there can be a high level of substitutability between different services. However, it also becomes clear that the use of the platforms without a prior check for correlation with visitor counts or route surveys and the general suitability as a data basis is only of limited use. GPSies and Outdooractive showed similarities with the count data in terms of visitor frequency at eleven count sites and can therefore be used for the Bavarian Forest National Park as a method to support the survey of spatial visitor behavior. However, it is not sufficient to carry out the validation against counting data only once. A systematic validation in regular time steps would be desirable, as the digital data resources may change dynamically.

4.2. Comparison with field observations

Visitor surveys and counts by human observers are very time-consuming and require a lot of planning (Arnberger et al., 2005; Fisher et al., 2018). On the other hand, counts by automatic counting devices provide insights into absolute visitor numbers at specific trail segments over longer periods of time, but often do not provide exact information about the activity performed (Bu et al., 2007; Cessford & Muhar, 2003). VGI can be a cost-effective and less time-consuming alternative that provides detailed information on spatiotemporal visitor behavior when highly correlated with existing count data. Thus, it is possible to find out which trails in a protected area are highly or lowly frequented, when, and for what visitor activity. In contrast to automatic counting devices, the entire course of the tour and the activity can be recorded (Norman et al., 2019). Passive data collection can also capture unauthorized activity better than an active collection method where the visitor may adjust their behavior due to the presence of park rangers (Heikinheimo et al., 2017; Norman et al., 2019; Cessford & Muhar, 2003). However, since the motives behind decisions as well as absolute visitor volumes are important for protected area administrations to develop appropriate management measures, a combination of several survey methods is recommended. Thus, the use of GNSS-based VGI data is conceivable as a complementary method besides route surveys and automated counting devices.

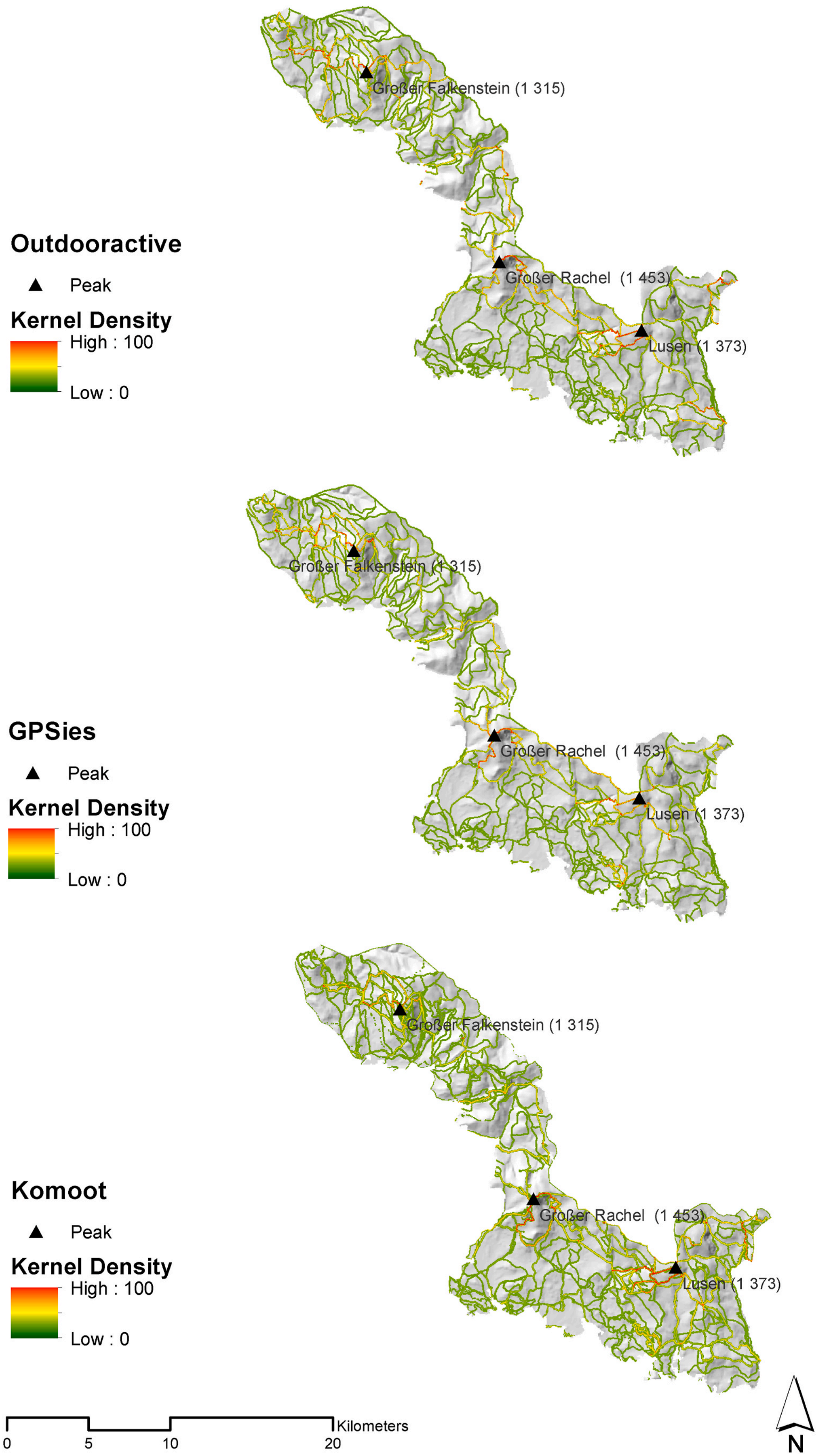

Fig. 3. Kernel density of hiking tours from GPSies, Outdooractive and Komoot on the territory of the Bavarian Forest National Park. (Source: gpsies.com 2019, outdooractive.com 2019, komoot.com 2019, NLPVW BW 2019, opendata.bayern.de 2019).

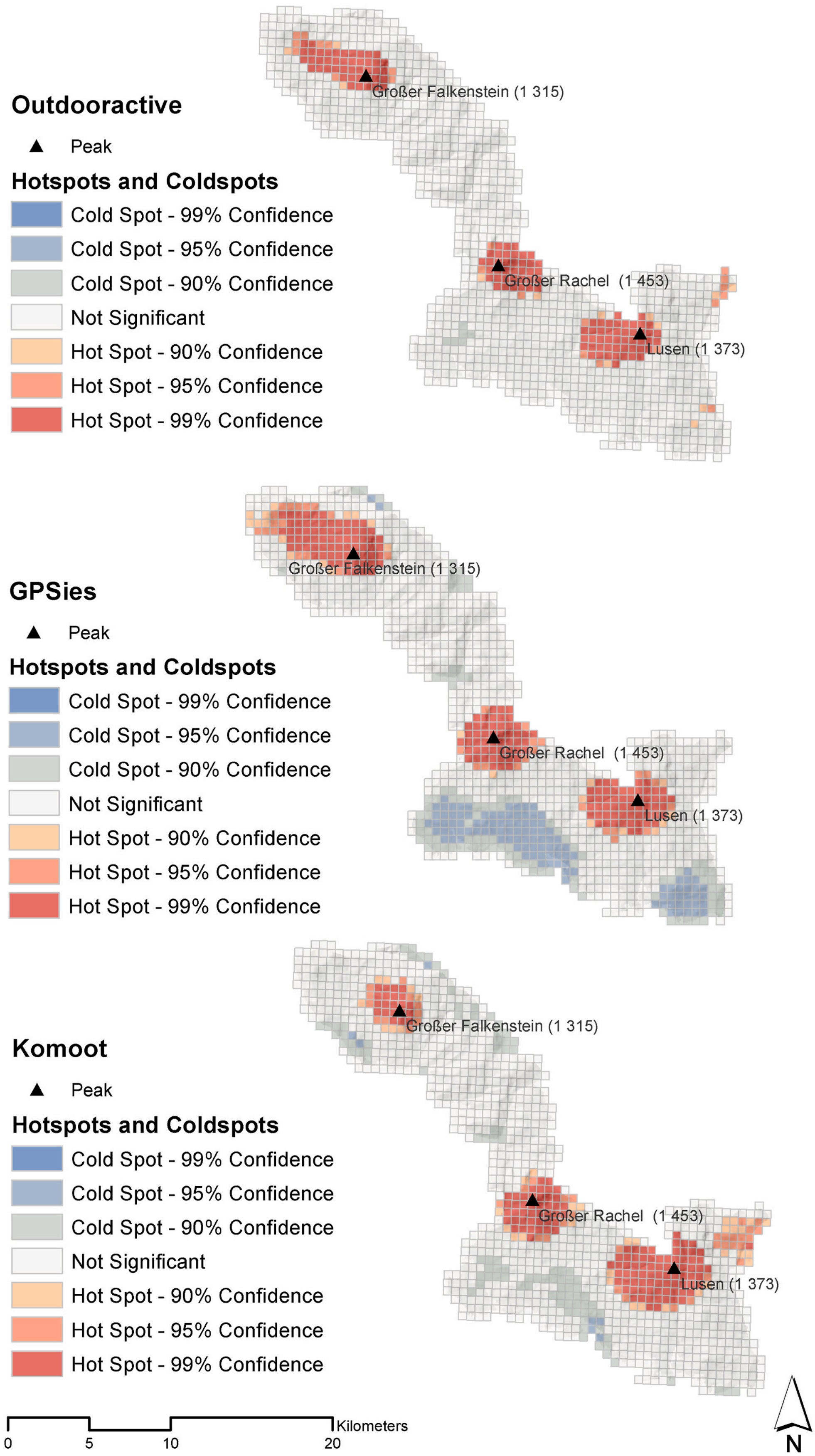

Fig. 4. Hotspot analysis of hiking tours from GPSies, Outdooractive and Komoot platforms on the territory of the Bavarian Forest National Park (Source: gpsies.com 2019, outdooractive.com 2019, komoot.com 2019, NLPVW BW 2019, opendata.bayern.de 2019).

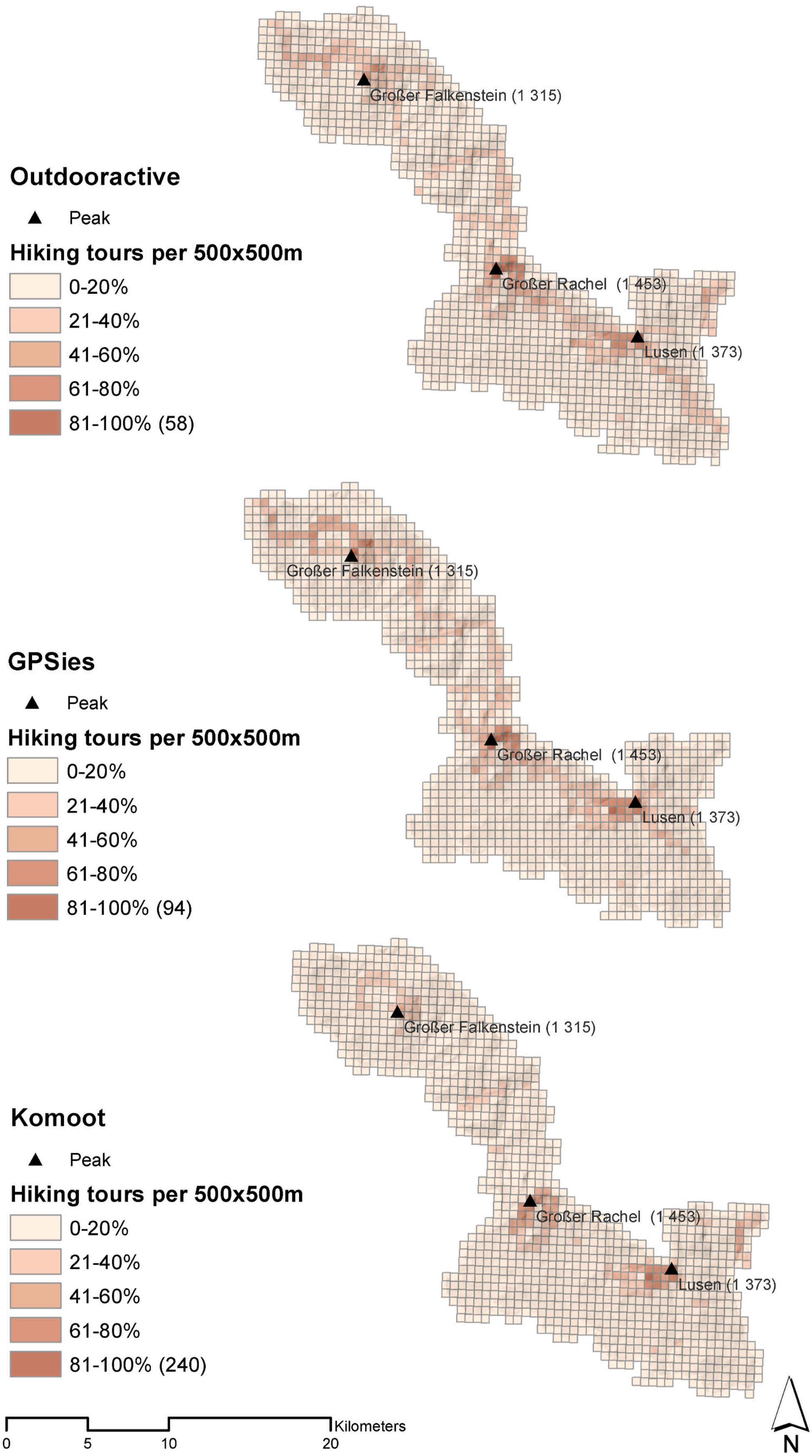

Fig. 5. Number of hiking tours from GPSies, Outdooractive and Komoot per 500 × 500m on the territory of the Bavarian Forest National Park (Source: GPSies.com 2019, outdooractive.com 2019, komoot.com 2019, NLPVW BW 2019, opendata.bayern.de 2019).

Table 4
Comparison of the spatial distribution of tours between 3 VGI platforms - correlation of tour numbers within specified grid units (n = 1159), based on data from GPSies, Outdooractive and Komoot. Analysis for six-year time period (2013–2018).

	Statistics	GPSies	Outdooractive	Komoot
GPSies	*Spearman correlation coefficient*	*1*	*0.928***	*0.817***
	N	*1159*	*1159*	*1159*
Outdooractive	*Spearman correlation coefficient*	*0.928***	*1*	*0.845***
	N	*1159*	*1159*	*1159*
Komoot	*Spearman correlation coefficient*	*0.817***	*0.845***	*1*
	N	*1159*	*1159*	*1159*

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 5
Correlation between number of GNSS-based VGI hiking tours and field counts at 11 counting locations, grouped by VGI data platform. Analysis of the data obtained for one-year time period (28.4.2013–27.4.2014).

	Statistics	Field counts
GPSies	*Spearman correlation coefficient*	*.633**
	Significance (2-tailed)	*.037*
	N	*11*
Outdooractive	*Spearman correlation coefficient*	*.261*
	Significance (2-tailed)	*.438*
	N	*11*
Komoot	*Spearman correlation coefficient*	-
	Significance (2-tailed)	-
	N	*No VGI-tours at 11 investigated locations between 28.04.13 – 27.04.14*

4.3. Strengths and limitations of the proposed methodology

When selecting the platforms to be used as a data basis, assessing their national and regional importance is crucial. A sufficient intensity of use in the respective country and therefore also for the number of available tours is decisive in appropriate platform selection (Norman & Pickering, 2017). The platforms used for this evaluation (GPSies, Outdooractive and Komoot), were selected due to their popularity among visitors in German protected areas. Nevertheless, remote protected areas have to be checked in advance with regard to the size of the available data (Norman et al., 2019). For the Bavarian Forest National Park, the three selected applications are the most popular among VGI platforms and may provide a potential data source for visitor monitoring. However, the results of our study indicate that GPSies and Outdooractive were more suitable for determining the distribution of visitors in the area concerned, since they reflected similar trends to the data collected in the field by the counting devices.

When using crowdsourced data, the privacy of users should also not be disregarded (Salganik, 2018). Data sources perceived as public therefore do not imply the unconditional consent of the author to use them for research (Salganik, 2018; Toivonen et al., 2019; Zook et al., 2017). For this study, only tours that were publicly available to any user of the platform were downloaded. The tours were analyzed only collectively and no personalized data was employed. Any possibility of drawing conclusions about individuals and their behavior, such as user-names, was excluded. Moreover, in the future, the focus on macro rather than micro data must be maintained when using similar data sources. The costs and benefits of a study must always be able to guarantee an appropriate ethical balance (Salganik, 2018).

When recording a tour using a GNSS-enabled device, there are factors that influence the strength of the signal and consequently the accuracy of the recorded track (Schamel, 2017). Since the Bavarian Forest National Park consists mainly of forest areas, deviations from the original route cannot be ruled out for some tours. However, it can be assumed that the impairment of the results by individual, deviating tours is low.

Further attention should be paid to the configuration of the GNSS-devices and the recording method of visitor movement trajectories. In the case of data recording, when using the constant time step, the speed of visitor movement affects the accumulation of trackpoints. Thus, this leads to a higher density of track-points at slow-motion locations and a possible bias in the kernel density and hotspot analysis, based on point datasets. According to this, the results would not be an indicator for the visitor density, but the length of stay. This could be the reason for the high trackpoint density in the summit area. However, it cannot be excluded that some applications automatically correct this source of error after recording a tour. More detailed investigations of this issue are needed to avoid it in the future.

The issue of spatial autocorrelation requires further attention. Spatial autocorrelation means that geographically closer areas are more similar in their characteristics (Brunsdon & Comber, 2015). This can be seen in the application of grid analysis in this study, where the study area is divided into grid cells that are given a certain weighting by the number of tours. Neighboring cells are more similar to each other than those that are far apart, as the tours show the linear movement of visitors. Spatial autocorrelation would also affect the observed strong positive correlation of the platforms with each other that occurred when the tour counts were compared. Therefore, when using this method in the future, a possible autocorrelation of the data should be checked. A remedy could be the measurement of the spatial autocorrelation based on object positions and object values. The result shows whether the pattern created by the objects is distributed, grouped or random (ESRI, 2018b).

The choice of the investigation period from January 1, 2013 to December 31, 2018 has to be critically reflected on. It was chosen to cover the collection period of the count data (28.4.2013–27.4.2014) and at the same time generate a sufficiently large dataset of GNSS-based VGI data. In the case of shorter study periods, such as annual comparisons, the sample size of tours would have been too small in order to obtain statistically stable results, especially for Outdooractive and Komoot. Supplementary material (S1; Figure A) presents dynamic changes in VGI platforms popularity and the number of annually uploaded tours. Longer study periods allow to mitigate temporal changes in the VGI dataset. Therefore, in subsequent studies of this type, a trade-off must always be made between the amount of data required and the desired target time period. Due to the growing popularity of the VGI platforms, it will be probably soon possible to investigate spatial behavior of visitors within smaller areas and shorter time bins, such as individual years, seasons or months.

Furthermore, in order to validate GNSS-based VGI data against field observations, long-term systematic visitor monitoring in protected areas is crucial. We admit, that having field count data for the entire study period (6 years; 2013–2018) would be an ideal situation. As our study is based upon existing historical data (VGI data and available field counts) no additional field data acquisition could have been considered at the stage of research design. Systematic field counts at 11 specified National Park locations were available for the period of 1 year (April 28, 2013 to April 27, 2014). After inspecting GNSS-based VGI-data uploaded during the same time period we encountered a problem of a limited sample size of tours available at specific VGI platforms. Supplementary material (S1, Table A) summarizes the number of annual visits (entries) registered in the field at 11 specified National Park locations and the number of VGI-tours crossing those points during corresponding time period. Regrettably, sample size of VGI-data was too small to validate it against available field count data and make final conclusions on VGI-data reliability. A significant positive correlation was found for GPSies platform. However, data sample size for Outdooractive and Komoot was not sufficient to make consistent comparison to the count data. On the other hand, at this point we would like to highlight the necessity of long-term visitor monitoring using other methods, such as automatic visitor counting in the field. Long-term systematic monitoring would allow better data basis to validate novel data acquisition approaches such as GNSS-based VGI.

4.4. Management implications

Our results may substantially support planning and management decisions related to outdoor recreational areas. Provisioning cost-efficient, reliable data resources on visitor spatial behavior is a current issue faced by scholars and practitioners. Both are operating in the context of rapid digitalization progress within social and environmental systems. Especially, ecologically sensitive recreational destinations may profit from high-resolution GNSS-based VGI data delivering useful information on the spatio-temporal patterns in recreational use. Such data might be useful for the prioritization of trail management, for example, closure of trails or level of maintenance of trails, use of trail signage; development of staff schedules, e.g. presence of rangers controlling on and off-site use of trails. Integration of GNSS-based data with additional information, such as environment structures, trail characteristics, external factors such as weather and trail conditions may multiply management and visitor benefits.

Yet, in order to make effective management decisions, reliable data is a key prerequisite. For many protected areas worldwide, these or similar GNSS-based VGI data are available. We present a way for other protected areas to assess the reliability of this digital data resources.

5. Conclusions

We conclude that GNSS-based VGI seems to offer new perspectives for visitor monitoring in protected areas. However, this type of data needs to undergo a strict validation procedure. In our case study, data provided by two of the investigated online platforms: "GPSies" and "Outdooractive" corresponded very well to each other in the spatial distribution of the recorded tours and lengths of hiking tours. Moreover, data obtained from GPSies showed a significant correlation with the count data collected in the field. The used analytical methods allowed quantitative comparisons of the spatial distribution patterns originating from various data platforms. Additionally, validation against field observations partly allowed us to assess the overall reliability of VGI data in visitor monitoring. Yet, due to limited VGI-data sample uploaded within the time frame of available field monitoring data, further investigation including longer field counting period is recommended.

Recent leisure and outdoor recreation trends show an increased use of technology among visitors. One such example of this is the recent rapid development of mobile phone applications dedicated to outdoor navigation and guidance, along with the progressing digitalization of recreational resources. Another important trend is the constantly growing interest in ICT and social media, used in a recreational context. Therefore, we believe that analyzing the digital traces of visitors may contribute to a better understanding of visitor flows in protected areas and support effective management of recreational use in vulnerable environments.

Credit author statement

Laura Horst: Investigation, Analysis; Visualisation, Writing- Original draft preparation; Writing- Reviewing and Editing; **Karolina Taczanowska**: Conceptualization, Methodology, Writing- Original draft preparation; Writing- Reviewing and Editing; Co-supervision; **Arne Arnberger**: Supervision; Statistical Analysis; Reviewing and Editing; **Florian Porst**: Coordination VGI data processing; Reviewing and Editing.

Acknowledgements

The research has been conducted in cooperation with the Bavarian Forest National Park, Germany. The authors wish to acknowledge the national park management for support, organizational help and provision of the downloaded VGI data resources. Field count data were collected within the research project "Socio-economic monitoring of the Bavarian Forest National Park", carried out by the University of Natural Resources and Life Sciences, Vienna. We owe special thanks to Hemma Preisel for sharing precise geolocation of counting devices and advice on the available geodata related to visitor monitoring in the Bavarian Forest National Park. We also thank Renate Eder and Maria Hußlein for their support for the research project and Marco Heurich for valuable comments and advice.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2022.102825.

References

Allex, B., Preisel, H., Eder, R., Hußlein, M., & Arnberger, A. (2016). Touristen im Nationalpark Bayerischer Wald: Die Rolle des Nationalparks für den Besuch, die Einstellung zum Schutzgebiet und ihr raumzeitliches Verhalten. In M. Mayer, & H. Job (Eds.), *Naturtourismus - Chancen und Herausforderungen, Studien zur Freizeit- und Tourismusforschung.* (pp. 187–196). Grafenau, Germany: Jahrestagung des Arbeitskreises für Tourismusforschung.

AllTrails. (2019). *GPSies ist ab sofort Teil von AllTrails. AllTrails-Hilfe*. https://support.alltrails.com/hc/de/articles/360029500751-GPSies-ist-ab-sofort-Teil-von-AllTrails.

AllTrails. (2022). AllTrails webservice. https://www.alltrails.com/de/. (Accessed 10 August 2022).

Arnberger, A., Allex, B., & Preisel, H. (2015). *Zusammenfassung der Auswertungsergebnisse—befragung und Besucherzählung im Nationalpark Bayerischer Wald.* Universität für Bodenkultur.

Arnberger, A., Haider, W., & Brandenburg, C. (2005). Evaluating visitor-monitoring techniques: A comparison of counting and video observation data. *Environmental Management, 36*(2), 317–327. https://doi.org/10.1007/s00267-004-8201-6

Arnberger, A., & Hinterberger, B. (2003). Visitor monitoring methods for managing public use pressures in the Danube Floodplains National Park, Austria. *Journal for Nature Conservation, 11*(4), 260–267. https://doi.org/10.1078/1617-1381-00057

Bell, S., Tyrväinen, L., Sievänen, T., Pröbstl, U., & Simpson, M. (2007). Outdoor recreation and nature tourism: A European perspective. *Living Reviews in Landscape Research, 1*, 46. https://doi.org/10.12942/lrlr-2007-2

Bielański, M., Taczanowska, K., Muhar, A., Adamski, P., González, L.-M., & Witkowski, Z. (2018). Application of GPS tracking for monitoring spatially unconstrained outdoor recreational activities in protected areas – a case study of ski touring in the Tatra National Park, Poland. *Applied Geography, 96*, 51–65. https://doi.org/10.1016/j.apgeog.2018.05.008

Brunsdon, C., & Comber, L. (2015). *An introduction to R for spatial analysis & mapping.* SAGE.

Buckley, R. (2003). Ecological indicators of tourist impacts in parks. *Journal of Ecotourism, 2*(1), 54–66. https://doi.org/10.1080/14724040308668133

Bu, F., Greene-Roesel, R., Diogenes, M., & Ragland, D. (2007). *Estimating pedestrian accident exposure: Automated pedestrian counting devices report, 23.* UC Berkeley: Safe Transportation Research & Education Center,Institute of Transportation Studies.

Bundesamt für Naturschutz. (2020). *BfN: Nationalparke*. https://www.bfn.de/themen/gebietsschutz-grossschutzgebiete/nationalparke.html.

Burns, R. C., Arnberger, A., & von Ruschkowski, E. (2010). Social carrying capacity challenges in parks, forests, and protected areas: An examination of transatlantic methodologies and practices. *International Journal of Sociology, 40*(3), 30–50. https://doi.org/10.2753/IJS0020-7659400302

Byczek, C., Longaretti, P.-Y., Renaud, J., & Lavorel, S. (2018). Benefits of crowd-sourced GPS information for modelling the recreation ecosystem service. *PLoS One, 13*(10), 1–23. https://doi.org/10.1371/journal.pone.0202645

Campelo, M. B., & Nogueira Mendes, R. M. (2016). Comparing webshare services to assess mountain bike use in protected areas. *Journal of Outdoor Recreation and Tourism, 15*, 82–88. https://doi.org/10.1016/j.jort.2016.08.001

Cessford, G., & Muhar, A. (2003). Monitoring options for visitor numbers in national parks and natural areas. *Journal for Nature Conservation, 11*(4), 240–250. https://doi.org/10.1078/1617-1381-00055

Creany, N. E., Monz, C. A., D'Antonio, A., Sisneros-Kidd, A., Wilkins, E. J., Nesbitt, J., & Mitrovich, M. (2021). Estimating trail use and visitor spatial distribution using mobile device data: An example from the nature reserve of orange county, California USA. *Environmental Challenges, 4*, Article 100171. https://doi.org/10.1016/j.envc.2021.100171

D'Antonio, A., & Monz, C. (2016). The influence of visitor use levels on visitor spatial behavior in off-trail areas of dispersed recreation use. *Journal of Environmental Management, 170*, 79–87. https://doi.org/10.1016/j.jenvman.2016.01.011

Di Minin, E., Tenkanen, H., & Toivonen, T. (2015). Prospects and challenges for social media data in conservation science. *Frontiers in Environmental Science, 3*, 6. https://doi.org/10.3389/fenvs.2015.00063

ESRI. (2016b). *Funktionsweise von "Kerndichte"—hilfe | ArcGIS for Desktop. Funktionsweise von "Kerndichte*. https://desktop.arcgis.com/de/arcmap/10.3/tools/spatial-analyst-toolbox/how-kernel-density-works.htm.

ESRI. (2018a). *Optimierte hot-spot-analyse—hilfe | ArcGIS desktop*. https://desktop.arcgis.com/de/arcmap/10.3/tools/spatial-statistics-toolbox/optimized-hot-spot-analysis.htm.

ESRI. (2018b). *Funktionsweise von räumlicher Autokorrelation (Global Moran's I)—hilfe | ArcGIS Desktop*. https://desktop.arcgis.com/de/arcmap/10.5/tools/spatial-statistics-toolbox/h-how-spatial-autocorrelation-moran-s-i-spatial-st.htm.

Fisher, D. M., Wood, S. A., White, E. M., Blahna, D. J., Lange, S., Weinberg, A., Tomco, M., & Lia, E. (2018). Recreational use in dispersed public lands measured using social media data and on-site counts. *Journal of Environmental Management, 222*, 465–474. https://doi.org/10.1016/j.jenvman.2018.05.045

Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *Geojournal, 69*(4), 211–221. https://doi.org/10.1007/s10708-007-9111-y

GPSies. (2019). *Über GPSies | GPSies. GPSies.com*. https://www.gpsies.com/page.do?page=about&language=de.

GPSies. (2019b). *GPSies | tracks, strecken, touren, routen, konverter*. GPSies.com. https://www.gpsies.com/analytics.do?mode=countries&language=de.

GPSies.com. n.d.). *GPSies | tracks, strecken, touren, routen, konverter*. GPSies.com. Retrieved November 20, 2019, from https://www.gpsies.com/analytics.do?mode=countries&language=de.

Gutzwiller, K. J., D'Antonio, A. L., & Monz, C. A. (2017). Wildland recreation disturbance: Broad-scale spatial analysis and management. *Frontiers in Ecology and the Environment, 15*(9), 517–524. https://doi.org/10.1002/fee.1631

Hadwen, W. L., Hill, W., & Pickering, C. M. (2007). Icons under threat: Why monitoring visitors and their ecological impacts in protected areas matters. *Ecological Management and Restoration, 8*(3), 177–181. https://doi.org/10.1111/j.1442-8903.2007.00364.x

Hallermann, M. (2019). *Reichweite und Targeting bei Komoot. Medium*. https://medium.com/komoot/reichweite-und-targeting-bei-komoot-9e374d55ab39.

Heikinheimo, V., Minin, E. D., Tenkanen, H., Hausmann, A., Erkkonen, J., & Toivonen, T. (2017). User-generated geographic information for visitor monitoring in a national park: A comparison of social media data and visitor survey. *ISPRS International Journal of Geo-Information, 6*(3), 85. https://doi.org/10.3390/ijgi6030085

Heikinheimo, V., Tenkanen, H., Bergroth, C., Järv, O., Hiippala, T., & Toivonen, T. (2020). Understanding the use of urban green spaces from user-generated geographic information. *Landscape and Urban Planning, 201*, Article 103845. https://doi.org/10.1016/j.landurbplan.2020.103845

Hennig, S. (2007). *EuRegionales Erholungsgebiet Nationalpark Berchtesgaden/Salzburger Kalkhochalpen—einblicke in das Monitoringsystem Erholungsnutzung, 8*. https://www.nationalpark-berchtesgaden.bayern.de/nationalpark/forschung/abgeschlossen/doc/euregio/ergebnisse_euregio_erholung.pdf.

Hennig, S., & Großmann, Y. (2008). Charakterisierung von Erholungsuchenden in Schutzgebieten im Fokus der Besucherlenkung am Beispiel des Nationalparks Berchtesgaden. *Mitteilungen - Frankische Geographische Gesellschaft, 55*, 97–122.

Holzmüller, M. (2011). *Lässige Gipfelstürmer. Süddeutsche.de*. https://www.sueddeutsche.de/karriere/existenzgruender-im-gespraech-3-laessige-gipfelstuermer-1.1057888.

Jiang, Y., Chen, L., Grekousis, G., Xiao, Y., Ye, Y., & Lu, Y. (2021). Spatial disparity of individual and collective walking behaviors: A new theoretical framework. *Transportation Research Part D: Transport and Environment, 101*, Article 103096. https://doi.org/10.1016/j.trd.2021.103096

Job, H., Fließbach-Schendzielorz, M., Bittlingmaier, S., Herling, A., & Woltering, M. (2019). *Akzeptanz der bayerischen Nationalparks: Ein Beitrag zum sozioökonomischen Monitoring in den Nationalparks Bayerischer Wald und Berchtesgaden, 122*. Würzburg University Press.

Jurado Rota, J., Pérez Albert, M. Y., & Serrano Giné, D. (2019). Visitor monitoring in protected areas: an approach to Natura 2000 sites using Volunteered Geographic Information (VGI). *Geografisk Tidsskrift-Danish Journal of Geography, 119*(1), 69–83. https://doi.org/10.1080/00167223.2019.1573409

Kidd, A. M., Monz, C., D'Antonio, A., Manning, R. E., Reigner, N., Goonan, K. A., & Jacobi, C. (2015). The effect of minimum impact education on visitor spatial behavior in parks and protected areas: An experimental investigation using GPS-based tracking. *Journal of Environmental Management, 162*, 53–62. https://doi.org/10.1016/j.jenvman.2015.07.007

Kim, J., Thapa, B., & Jang, S. (2019). GPS-based mobile application: An alternative tool to assess spatio-temporal patterns of visitors' activities in a national park. *Journal of Park and Recreation Administration, 37*(1). https://doi.org/10.18666/JPRA-2019-9175

Komoot. (2019). *About komoot | the world's leading outdoor app*. Komoot. https://www.komoot.com/about.

Komoot. (2020a). *Highlights und smart tours*. Komoot. https://support.komoot.com/hc/de/articles/360023103612-Highlights-und-Smart-Tours.

Komoot. (2020b). *Bestimmen wer deine Touren sehen kann*. komoot. https://support.komoot.com/hc/de/articles/360023355331-Bestimmen-wer-deine-Touren-sehen-kann.

Komoot. (2020c). *Sichtbarkeit deines Profils bestimmen*. komoot. https://support.komoot.com/hc/de/articles/360023355191-Sichtbarkeit-deines-Profils-bestimmen.

Koomot. (2022). Komoot webservice. URL: https://www.komoot.de/jobs. (Accessed 10 October 2022).

Korpilo, S., Virtanen, T., & Lehvävirta, S. (2017). Smartphone GPS tracking—inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning, 157*, 608–617. https://doi.org/10.1016/j.landurbplan.2016.08.005

Krebs, P., & Duncan, D. T. (2015). Health app use among US mobile phone owners: A national survey. *JMIR MHealth and UHealth, 3*(4), 101. https://doi.org/10.2196/mhealth.4924

IUCN. (2018). Tourism and visitor management in protected areas: Guidelines for sustainability. In Y.-F. Leung, A. Spenceley, G. Hvenegaard, & R. Buckley (Eds.), *IUCN, international union for conservation of nature*. https://doi.org/10.2305/IUCN.CH.2018.PAG.27.en

Levin, N., Lechner, A. M., & Brown, G. (2017). An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas. *Applied Geography, 79*, 115–126. https://doi.org/10.1016/j.apgeog.2016.12.009

Monz, C., Creany, N., Nesbitt, J., & Mitrovich, M. (2021). Mobile device data analysis to determine the demographics of park visitors. *Journal of Park and Recreation Administration, 39*(1).

Monz, C., Mitrovich, M., D'Antonio, A., & Sisneros-Kidd, A. (2019). Using mobile device data to estimate visitation in Parks and protected areas: An example from the nature reserve of orange County, California. *Journal of Park and Recreation Administration, 37*(4), 92–109. https://doi.org/10.18666/JPRA-2019-9899

Muhar, A., Brandenburg, C., & Arnberger, A. (2005). *Kongressbericht "Umwelt, Naturschutz und Sport im Dialog": Sport in Schutzgebieten ; 2. Kongress an der Deutschen Sporthochschule Köln vom 13. - 14. September 2004* (I. für N. und Ö. (INÖK) Köln Deutsche Sporthochschul. In *e, 17*. https://books.google.de/books?id=TBLAMAAACAAJ.

Nationale Naturlandschaften. (2020). *Nationalpark bayerischer Wald*. Nationale naturlandschaften. https://nationale-naturlandschaften.de/gebiete/nationalpark-bayerischer-wald.

Nationalparkverwaltung Bayerischer Wald. (2014). *Grenzenlose waldwildnis entdecken*. Grafenau. https://www.nationalpark-bayerischer-wald.bayern.de/service/downloads/doc/faltblatt/grenzenlose_waldwildnis.pdf.

Norman, P., & Pickering, C. M. (2017). Using volunteered geographic information to assess park visitation: Comparing three on-line platforms. *Applied Geography, 89*, 163–172. https://doi.org/10.1016/j.apgeog.2017.11.001

Norman, P., Pickering, C. M., & Castley, G. (2019). What can volunteered geographic information tell us about the different ways mountain bikers, runners and walkers use urban reserves? *Landscape and Urban Planning, 185*, 180–190. https://doi.org/10.1016/j.landurbplan.2019.02.015

Outdooractive. (2019a). Modernste Kartentechnologie für den Outdoorbereich. https://www.outdooractive.com/de/map-information.html.

Outdooractive. (2019b). *Über uns*. Corporate Outdooractive. https://corporate.outdooractive.com/de/unternehmen/.

Outdooractive. (2022). Outdooractive webservice. URL: https://corporate.outdooractive.com/de/plattform/. (Accessed 10 August 2022).

Pickering, C., Rossi, S. D., Hernando, A., & Barros, A. (2018). Current knowledge and future research directions for the monitoring and management of visitors in recreational and protected areas. *Journal of Outdoor Recreation and Tourism, 21*, 10–18. https://doi.org/10.1016/j.jort.2017.11.002

Porst, F., Bečka, P., Kučeravá, B., Štemberk, J., Allex, B., Arnberger, A., Eder, R., & Preisel, H. (2020). *Grenzüberschreitendes sozioökonomisches Monitoring in den nationalparken bayerischer Wald und šumava in den jahren 2017-2019 (1*. Auflage.

Runtastic. (2020). *Adidas runtastic: Adidas running & adidas training apps*. https://www.runtastic.com/de/.

Rupf, R., Wyttenbach, M., Köchli, D., Hediger, M., Lauber, S., Ochsner, P., & Graf, R. (2011). Assessing the spatio-temporal pattern of winter sports activities to minimize disturbance in capercaillie habitats. *Journal on Protected Mountain Areas Research and Management, 3*, 23–32. https://doi.org/10.1553/eco.mont-3-2s23

Ruths, D., & Pfeffer, J. (2014). Social media for large studies of behavior. *Science, 346* (6213), 1063–1064. https://doi.org/10.1126/science.346.6213.1063

Salganik, M. J. (2018). *Bit by bit: Social research in the digital age*. Princeton University Press.

Schamel, J. (2017). Ableitung von Präferenzen aus GPS-Trajektorien bei landschaftsbezogenen Erholungsaktivitäten. *AGIT - Journal für Angewandte Geoinformation, 9*.

See, L., Mooney, P., Foody, G., Bastin, L., Comber, A., Estima, J., Fritz, S., Kerle, N., Jiang, B., Laakso, M., Liu, H.-Y., Milčinski, G., Nikšič, M., Painho, M., Pődör, A., Olteanu-Raimond, A.-M., & Rutzinger, M. (2016). Crowdsourcing, citizen science or volunteered geographic information? The current state of crowdsourced geographic information. *ISPRS International Journal of Geo-Information, 5*(5), 55. https://doi.org/10.3390/ijgi5050055

Skov-Peterson, H., & Gimblett, H. R. (2008). In H. R. Gimblett, & H. Skov-Peterson (Eds.), *Monitoring, simulation, and management of visitor landscapes: Vol. Introduction: Monitoring, simulation and management of visitor landscapes*. USA: University of Arizona Press.

Strava. (2020). *Strava | Tracking von Lauf- und Radfahraktivitäten im sozialen Netzwerk für Sportler*. https://www.strava.com/about.

Švajda, J., Masný, M., Koróny, S., Mezei, A., Machar, I., & Taczanowska, K. (2018). Visitor profiling using characteristics of socio-demographic and spatial behavior as tools to support the management of protected mountain areas. http://hdl.handle.net/20.500.11956/169450.

Sykes, J., Hendrikx, J., Johnson, J., & Birkeland, K. W. (2020). Combining GPS tracking and survey data to better understand travel behavior of out-of-bounds skiers. *Applied Geography, 122*, Article 102261. https://doi.org/10.1016/j.apgeog.2020.102261

Taczanowska, K., González, L.-M., Garcia-Massó, X., Muhar, A., Brandenburg, C., & Toca-Herrera, J.-L. (2014). Evaluating the structure and use of hiking trails in recreational areas using a mixed GPS tracking and graph theory approach. *Applied Geography, 55*, 184–192. https://doi.org/10.1016/j.apgeog.2014.09.011

Taczanowska, K., Muhar, A., & Arnberger, A. (2008). In H. R. Gimblett, & H. Skov-Peterson (Eds.), *Exploring spatial behaviour of individual visitors as background for* *agent-based simulation: Vol. Monitoring, simulation, and management of visitor landscapes*. University of Arizona Press.

Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H., & Di Minin, E. (2019). Social media data for conservation science: A methodological overview. *Biological Conservation, 233*, 298–315. https://doi.org/10.1016/j.biocon.2019.01.023

Under Armour. (2021). *MapMyFitness*. Under Armour. https://www.mapmyfitness.com/.

Wolf, I. D., Brown, G., & Wohlfart, T. (2018). Applying public participation GIS (PPGIS) to inform and manage visitor conflict along multi-use trails. *Journal of Sustainable Tourism, 26*(3), 470–495. https://doi.org/10.1080/09669582.2017.1360315

Zook, M., Barocas, S., boyd, danah, Crawford, K., Keller, E., Gangadharan, S. P., Goodman, A., Hollander, R., Koenig, B. A., Metcalf, J., Narayanan, A., Nelson, A., & Pasquale, F. (2017). Ten simple rules for responsible big data research. *PLoS Computational Biology, 13*(3), 10. https://doi.org/10.1371/journal.pcbi.1005399