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Assessing the potential of social media for estimating recreational use of urban and peri-urban forests

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ABSTRACT

Social forest functions including recreation are important for increasingly urbanised societies. For effective management of forest recreation areas, monitoring visitor frequencies is crucial. Increasingly, attempts are being made to incorporate recreational use data into National Forest Inventories (NFI), but given the large scale of national assessments, such data is often elusive. In this study we explore the potential of geotagged social media data for assessing visitor frequencies and explore recreational activities through text-based social media data. We analysed data from Twitter, Flickr and Instagram, both at local scale for 10 NFI forest sites, as well as at national scale to assess recreational use. Data availability was significantly correlated between the three platforms, even though absolute counts differed markedly. The model of recreational visitation based on social media data correlated significantly with an existing potential recreational model, indicating that social media data are a valid source of information for recreational use and can be used in future studies to assess recreational potential. Although data availability limits assessments for small areas of forests, large scale assessments using social media are feasible, and provide a potentially more empirically grounded assessment of recreational potential than theoretical models alone. We suggest that future work should aim at integrating social media data into traditional theoretical recreational models as part of a method triangulation, particularly for areas where recreational usage by visitors is high, but population counts are low. However, because social media data are provided by commercial platforms, we believe that more research is needed into harvesting and analysing other forms of content generated by users to decrease the dependency on commercial social media platforms that may or may not be available in the long run, and can be run locally or through central organisations involved in forest and landscape monitoring and observation.

1. Introduction

The relationship of people to forests, especially in increasingly densely populated urbanised societies, is changing. Social functions including recreation, health and well-being and quality of life (Pröbstl et al., 2010) are increasingly important. For effective management of natural recreation areas, including forests, visitor monitoring is crucial. Knowing the number of visitors and their activities is needed to assess visitor impacts, plan facilities, allocate budgets and personal resources and guide policy and management (Cope et al., 2000; Hadwen et al., 2007; Loomis, 2000). Baseline visitation rates are indispensable for evaluating the effect of management actions (Loomis, 2000). In addition, visitor monitoring can serve to identify conflicts between visitor groups, potential problem 'hotspots' in recreation areas and future trends (Cessford and Muhar, 2003). Cope et al. (2000) distinguish between three components of visitor monitoring: visitor counting, visitor profiling (e.g. according to sociodemographic measures) and surveying of visitor opinions. The focus of the present study is on the first component, the estimation of visitor frequencies.

Methods for estimating the number of visitors include using automatic counters, camera recordings, self-counting techniques such as voluntary registration, direct observation by staff observers, questionnaire surveys, proxy measures such as permits and entrance fees where applicable, from which use can be estimated, GPS and smartphone tracking and remote sensing (Arnberger et al., 2005; Cessford and Muhar, 2003; Rupf and Wyttenbach, 2019; Wolf et al., 2012). However,

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most of these techniques can only be used locally. They are resource intensive, requiring funding, staff expertise and availability – constraints that often limit effective visitor monitoring (Hadwen et al., 2007). At larger spatial and temporal scales, these approaches can quickly become cost-prohibitive to implement (English et al., 2002).

Of all natural areas, forests belong to the most important areas for people to recreate (Pröbstl et al., 2010). Over the last century, National Forest Inventories (NFIs) have become an established source for county-wide information on forests (Tomppo et al., 2010; Vidal et al., 2010). Modern NFIs use statistical sampling designs, mostly with plots on systematic grids covering whole countries (Lawrence et al., 2010), providing information on the current state and development of the forest (Barreiro et al., 2016; Lanz et al., 2019). In line with the increasing relevance of forests for recreation, attempts are being made in some countries to integrate social and recreational indicators into NFIs, although for the most part, detailed information is still elusive (Atkinson et al., 2020). In the Swiss NFI, potential recreational demand (PRD) is currently predicted using a model based on the distance to settlements and census data (Brändli and Ulmer, 2001). The result is a map of Switzerland showing forest areas with varying PRD. The model focuses on nearby recreation and on holidays with overnight stays – day excursions are beyond its scope. Furthermore, proximity to densely populated settlements is not the only criterion whether a forest is frequently visited or not. For example, a forest plot might be near a tourist resort and therefore exhibit a high potential for recreation according the model, but frequentation might be low because the main hiking trail leading to a viewpoint does not pass through this forest plot. In order to reliably estimate visitor frequencies in forests, a triangulation of methods is therefore needed. In the following, we introduce an increasingly popular approach to gather information on forest visitation and recreation using data harvested from social media.

In recent years, large volumes of data have been created by social media users, often including uploaded user-generated photographs or texts that have been referenced with geographic coordinates (Norman and Pickering, 2017; Tenkanen et al., 2017; Wood et al., 2013). Daume et al. (2014) advocate complementing forest monitoring approaches such as NFIs and long-term and large-scale Forest Observational Studies by social media data. Such data reveal actual spatial patterns of visitation that have been found to match observations from traditional survey methods used for recreational visitor monitoring (Donahue et al., 2018; Heikinheimo et al., 2017; Sessions et al., 2016; Sonter et al., 2016; Wood et al., 2013).

For example, a study about over 800 highly popular recreational areas worldwide showed a consistent and statistically significant relation between field-based visitor counts and a measure of visitation calculated based on user-uploaded photographs from the Flickr (www.flickr.com) platform (Wood et al., 2013). This measure is calculated on uploaded photographs as the number of days a user spent within a certain recreation area (i.e. the number of days a user uploaded at least one photograph). However, the relationship between the measure based on Flickr photographs and *in situ* counts differed considerably between different recreational areas. Therefore, Wood et al. (2013) recommend only estimating relative changes in visitor numbers using social media data from Flickr.

Another study used georeferenced Flickr photographs to estimate visitor frequencies in protected areas in Vermont (US), which correlated significantly with *in situ* counts (Sonter et al., 2016). Based on these correlations, researchers estimated overall visitor counts for years in which no *in situ* counts had been collected. However, the model showed low explanatory power ($R^2 = 0.22$), which the authors assume is based on the high variability of activities and visitor demographics over time that impacts visitation frequencies (Sonter et al., 2016). Other studies found that social media data were able to explain over 60 % of the variance observed in field-based visitor counts. Examples range from a Finnish national park estimated based on Instagram (Heikinheimo et al., 2017), over visitor counts to lakes in Iowa and Minnesota estimated from Flickr (Keeler et al., 2015), and urban green spaces in Minnesota based on Flickr and Twitter data (Donahue et al., 2018). A study in different US national parks found that the relation between Flickr photograph counts and visitor counts was higher in highly frequented parks than in parks with lower visitor frequencies (Sessions et al., 2016). Studies comparing estimates from different social media platforms found relative estimates between different social media platforms comparable, for instance between Flickr and Twitter for estimating urban park visitation rates (Donahue et al., 2018).

There is a growing body of literature harnessing social media data for visitor counts, with technology and availability of new data sources changing where and how visitors can be monitored (Pickering et al., 2018). The focus of this research has so far been mostly on protected areas, with a view of improving protected area management. Furthermore, social media data have mostly been assessed for highly frequented parks of international renown, such as Yellowstone NP (Wood et al., 2013), or highly frequented urban parks and urban forests (Chen et al., 2018b; Korpilo et al., 2017). Urban and peri-urban forests and green spaces – very important everyday recreational sites, but with lower absolute visitor numbers than internationally renowned parks or central urban park areas, have so far received less attention (Norman and Pickering, 2017). A methodological comparison in a Dutch peri-urban green space showed that social media data has the potential to complement traditional survey and participatory mapping data collected *in situ* (Komossa et al., 2020). In this study, we assess whether social media data can also be used for investigating recreational use of less studied urban and peri-urban forests.

The aim of the study was two-fold: First, we aimed to assess the potential of using social media data to estimate visitor frequencies at selected forest sites as a way of including visitation data in NFIs. Second, we aimed to assess the potential for using social media as part of a triangulation of methods to improve estimations of use frequency on a national scale. To this end, our study addresses the following research questions:

- RQ1: How does the availability of social media data in urban and peri-urban forests compare across different social media platforms and selected forest sites? Can the data be used to estimate use frequencies?
- RQ2: What additional information about usage and activities in urban and peri-urban forests can we gain from analysing textual content of social media data?
- RQ3: How does an assessment of social media data as an indicator of recreational use compare to a theoretical model based on census data and accessibility (the PRD-model) on a national scale?

In order to address these research questions, we conducted a case study in Switzerland, which we introduce in the following.

2. Methods

In order to assess the potential of social media data for estimating recreational use of forests we combine three different methodological approaches (Fig. 1).

Firstly, for a sample of ten forest study sites in Switzerland we assess data availability on three different social media platforms and compare the available data between sites and platforms. Secondly, apart from enumerating available amount of content between forest sites and platforms, we also analyse and compare semantic content in the form of text data across three different forests. Finally, we calculated a model of recreation based on social media data and compare it to an existing model of potential recreation demand based on census data and accessibility. This comparison allows us to gage the usability of social media data for forest recreation research. In the following, we describe our methodological approach in more detail.

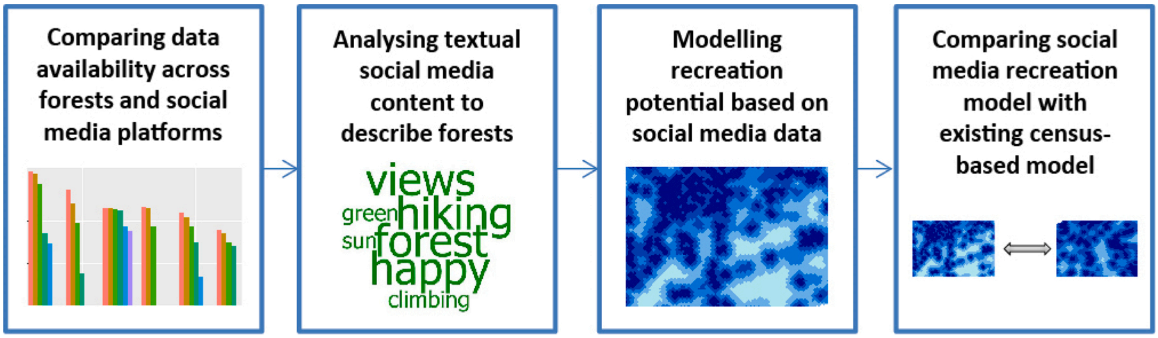

Fig. 1. Overview of methodological approach.

2.1. Selection of study sites

We based our selection of study sites on the location of the sample plots of the Swiss National Forest Inventory (Schweizerisches Landesforstinventar LFI, www.lfi.ch), which uses a systematic sampling grid (1.4 km x 1.4 km), covering the whole of Switzerland (Lanz et al., 2019) with about 6500 plots located in forest. From these NFI plots, we choose a small subsample of 10 study sites across Switzerland that were characterised by different conditions in terms of forest composition, population density in nearby settlements and type of recreational use (Table 1). All sites showed a high recreational use potential according to the model for potential recreation demand used by the Swiss NFI (Brändli and Ulmer, 2001). Of our ten sites, three (Zurich Dolder, Aarau, Ebmatingen) were already part of a pilot project aiming at linking socio-cultural forest monitoring with NFI data (Hegetschweiler et al., 2017). To our sample we added seven other sites (Zurich Uetliberg, Neuchâtel, Ovronnaz, Locarno, Arosa, Scuol, S-chanf). At the time of the study, these sites were being considered as potential locations for a major forest visitor survey (Hegetschweiler et al., 2021). As NFI plots are not always located on pathways or near other recreational infrastructure we chose an initial radius of 5000 m around the NFI plots for including recreational activities in the NFI data. We then subsequently tested for the influence of our search radius on data availability by using circles of 250 m, 500, 1000, 2000, 3000, 4000 and 5000 m, respectively.

2.2. Harvesting data from different social media platforms

For comparative reasons we chose to investigate three different social media platforms, namely Instagram, Flickr and Twitter as three widely known platforms commonly used in research on recreation and cultural ecosystem services (Chen et al., 2018a; Figueroa-Alfaro and Tang, 2017; Guerrero et al., 2016; Tenkanen et al., 2017). Instagram (www.instagram.com) is a social network that focuses on image sharing, with the data containing photos that are optionally tagged with keywords and/or georeferenced to a location ('geotagged'). Flickr (www.flickr.com) is a photo-sharing website, where data contain photos that have optionally been described through short texts, title, tags, and/or geotags. Twitter is a social media platform focusing on short texts known as microblogs ('tweets'), with data sometimes containing optional images and geotags. As selection criteria, all data used for this study had to be geotagged so that we could conduct spatial analysis on the distribution of social media data regarding forests.

At the time of conducting this study, all three social media platforms still allowed the usage of their data through Application Programming Interfaces (APIs) of the platforms, which allowed spatial queries to be made. We used the Netlytic platform to access social media content from Instagram (Gruzd, 2020). We did not specify any keywords for our search, but rather collected all data contained within our search radius of 5000 m around selected study sites (note that the regions for the two Zurich sites thus overlap). The data collection period was between October 2017 and January 2018 (Flickr: Oct 09. 2017 - Jan 26. 2018; Twitter Oct 09. 2017 - Oct 27. 2017; Oct 31. 2017 - Nov 06. 2017; Nov 22. 2017 - Jan 07. 2018; Instagram: Oct 06. 2017 - Nov 05. 2017; Nov 22. 2017 - Jan 25. 2018). Autumn is a popular time to visit Swiss forests, and although forest visit frequency is generally lower in winter than in summer (Hunziker et al., 2012), a recent forest visitor survey revealed hardly any differences in characteristics between winter and summer visitors to forests (Hegetschweiler et al., 2021). Forests used for nearby recreation are popular all year round in Switzerland and mountainous forests are popular for winter hiking and snowshoeing during the winter. The breaks in the data collection period for Twitter and Instagram occurred due to server errors. We filtered harvested data for duplicates

Table 1
Characterisation of study sites in terms of forest type, dominant tree species, stand structure, urbanity and recreation type.

Site	Type of forest	Dominant tree species	Stand structure	Production region*	Urbanity (BFS., 2017)	Main type of recreation
Zurich Dolder	Mixed	*Fagus sylvatica* (beech) *Picea abies* (Norway spruce)	Multi-layered	Plateau	Urban	Nearby recreation
Zurich Uetliberg	Deciduous	*Fagus sylvatica* (beech)	Multi-layered	Plateau	Urban	Nearby recreation
Aarau	Deciduous	Various broadleaved species	Multi-layered	Plateau	Urban	Nearby recreation
Ebmatingen	Coniferous	*Picea abies* (Norway spruce)	Multi-layered	Plateau	Peri-urban	Nearby recreation
Neuchâtel	Mixed	*Fagus sylvatica* (beech) *Picea abies* (Norway spruce)	Multi-layered	Jura	Urban	Nearby recreation
Locarno	Deciduous	*Castanea sp.* (chestnut) *Quercus sp.* (oak)	Single-layered	Southern Alps	Urban	Tourism
Arosa	Coniferous	*Picea abies* (Norway spruce)	Single-layered	Alps	Peri-urban	Tourism
Scuol	Mixed	*Fraxinus excelsior* (European ash) *Picea abies* (Norway spruce)	Multi-layered	Alps	Peri-urban	Tourism
S-chanf	Coniferous	*Picea abies* (Norway spruce) *Larix decidua* (European larch)	Single-layered	Alps	Rural	Tourism
Ovronnaz	Coniferous	*Abies alba* (Silver fir)	Stratified	Alps	Rural	Tourism

* Classification of Switzerland into the regions Jura, Plateau, Pre-Alps, Alps and Southern Alps according to their different conditions of growth and wood production.

and other errors such as missing coordinates. In total, we harvested 2590 geotagged photos from Flickr, 4106 from Twitter and 208,285 from Instagram. This distribution already indicates considerable differences in the availability of data for the different platforms, which we analyse in more detail below.

2.3. Analysing the distribution of data availability at different sites for different platforms

First, we analysed data availability between different study sites and for different platforms, calculating the number of harvested data points per site and platform. To gage the relationship between data availability at different social media platforms, we compared data availability for different study sites using Spearman correlation. As a further analysis, we calculated data availability for different radii among the study locations in order to provide a more detailed picture of data availability as a function of increasing distance, using circles with 250 m, 500, 1000, 2000, 3000, 4000 and 5000 m.

2.4. Text content analysis of social media data

To analyse the semantic content of social media data, we extract the words users describe their uploaded images with (referred to as 'tags' in Flickr, or 'hashtags' in Instagram). Tags/hashtags consist of natural language terminology that users apply to help other users find their uploaded content, which in turn will lead to comments and/or likes on their uploaded photographic content, which increases their social capital on these platforms. This creates an incentive for users to apply tags and also to tag images with words that are widely understood and make sense to other users. The terms used as tags can therefore often be classified as what is known in cognitive psychology as the 'basic level' (Rorissa, 2008; Tversky and Hemenway, 1983). Tag-based descriptions fulfil an important function on social media and an analysis of the content of Flickr, for instance showed that most users diligently apply tags to their photographic content (Hollenstein and Purves, 2010). Researchers have harvested and analysed such textual user-generated content for describing how people perceive places and landscapes before (Derungs and Purves, 2016; Dunkel, 2015; Hollenstein and Purves, 2010). In this study, we focus on three forest sites as peri-urban forests located in three different language areas in Switzerland (German-speaking: Zürich Uetliberg, French-speaking: Neuchâtel and Italian-speaking: Locarno) to explore textual descriptions using Instagram data. We chose Instagram as data source for this exploratory analysis because compared with Flickr and Twitter, more data were available. For each of the three study locations, we used the geotagged Instagram data available within a radius of 5000 m and extracted only those contained within forest polygons (using the NFI forest map (Waser et al., 2015)). From the data thus selected we complied word lists consisting of all the tags for all the posts. In this exploratory work, our focus was on English, as this allowed comparison across the three sites. From these lists we removed English stop-words, such as 'it, she, he, them, the, or, and', a commonly applied filtering method in the field of natural language processing (Manning and Schütze, 1999). To visualise the data, we enumerated frequencies for each term and displayed the most frequent terms in word clouds. A first analysis of highly frequent terms indicated that place names are very prominently used in tags, consistent with previous studies analysing social media tag content (Jones et al., 2008). As we were not interested in this study in exploring how forest areas were named, we manually filtered place names from the lists. We then extracted English terms relevant for landscape descriptions based on existing lists of terms that informed from psychological research (Tversky and Hemenway, 1983). A former study (Purves et al., 2011) classified the most frequently used English terms describing place into three groups: *elements* (visible elements forming part of the perceived landscape such as rivers, mountains, houses, cars etc), *qualities* (perceptual qualities inferred from the environment green, bright, cold), and *activities* (such as hiking, cycling, walking). We retained terms used at least twice at every study site, filtering out the long tail of terms used only once. Using the final list of filtered terms allowed us to qualitatively describe and compare the three study sites.

2.5. Comparing estimates for recreational use from social media data with the potential recreation demand model

To answer our third research question, we compare the estimated recreational use based on social media with an existing model for potential recreation demand that was developed for application within the Swiss NFI (PRD-model) (Brändli and Ulmer, 2001). Although the focus of the PRD-model was on forests, the model was calculated over the entire surface area of Switzerland. Consequently, we also harvested social media data for the same spatial extent. For this part of our study we used Twitter and Flickr data available for all of Switzerland and excluded Instagram data, which were cost-prohibitive to obtain at national scale. At national scale, we found more data on Twitter than on Flickr, with both platforms exhibiting similarities in the spatial distribution of the data concentrated around urban centres. We calculated two different models, one based on Twitter and one based on Flickr data for all of Switzerland. We used the same cells as the PRD-model, which are in turn based on the 1.4 km grid spacing of the NFI. Most cells did not contain any data from social media, yielding counts of social media data of 0, which poses problems for our model estimations and statistical analyses. For every cell in our study area, we therefore calculated the mean distance to the nearest 10 data points in Twitter and Flickr, respectively, which allowed appropriate modelling and statistical analyses. We chose the ten nearest social media points in order to smooth the effects of individual social media posts. We then calculated a Generalised Least Squared-regression model (Beguería and Pueyo, 2009) between the measure 'mean distances to ten nearest social media data points' and the estimated potential recreation demand based on the PRD-model. In order to assess the model fit across space, we mapped residuals for both the Flickr and Twitter-based model. A visual inspection of the residuals indicated the presence of spatial autocorrelation. We thus calculated Moran's *I* values (Moran, 1948) and found significant values in both the distribution of Twitter and Flickr data as well as values of estimated recreation use based on these datasets. As the datasets were too large to take into account the correlation structure across the whole dataset, we randomly selected 5% of the data and tested 4 different correlation structures (rational quadratic, exponential, Gaussian and spherical). We obtained the best results using a rational quadratic correlation structure and therefore selected this method. Computational limitations demanded we used 10 random subsets of 10 % of the data for calculations. We visualised the results of these correlations on a map using a "natural breaks" algorithm to split the values into 5 distinct groups.

3. Results

3.1. Availability and distribution of social media data in urban and peri-urban forests

The distribution of data points for different platforms indicates considerable differences between different platforms, with Instagram counts several orders of magnitude larger than Twitter or Flickr (Fig. 2). The differences are consistent for all study sites, but are particularly noteworthy for the two urban forests in Zurich (Zurich Dolder and Uetliberg). The buffers of these two urban forests overlap, and the high counts are explained by social media posts outside of the forest in the touristic centre of Zurich.

Despite differences between the sample size harvested from different platforms, the data sets were all significantly correlated (Twitter vs. Instagram (Spearman's ρ: 0.964; $p < 0.01$), Instagram vs. Flickr (Spearman's ρ: 0.818; $p < 0.01$) and Flickr vs. Twitter (Spearman's ρ:

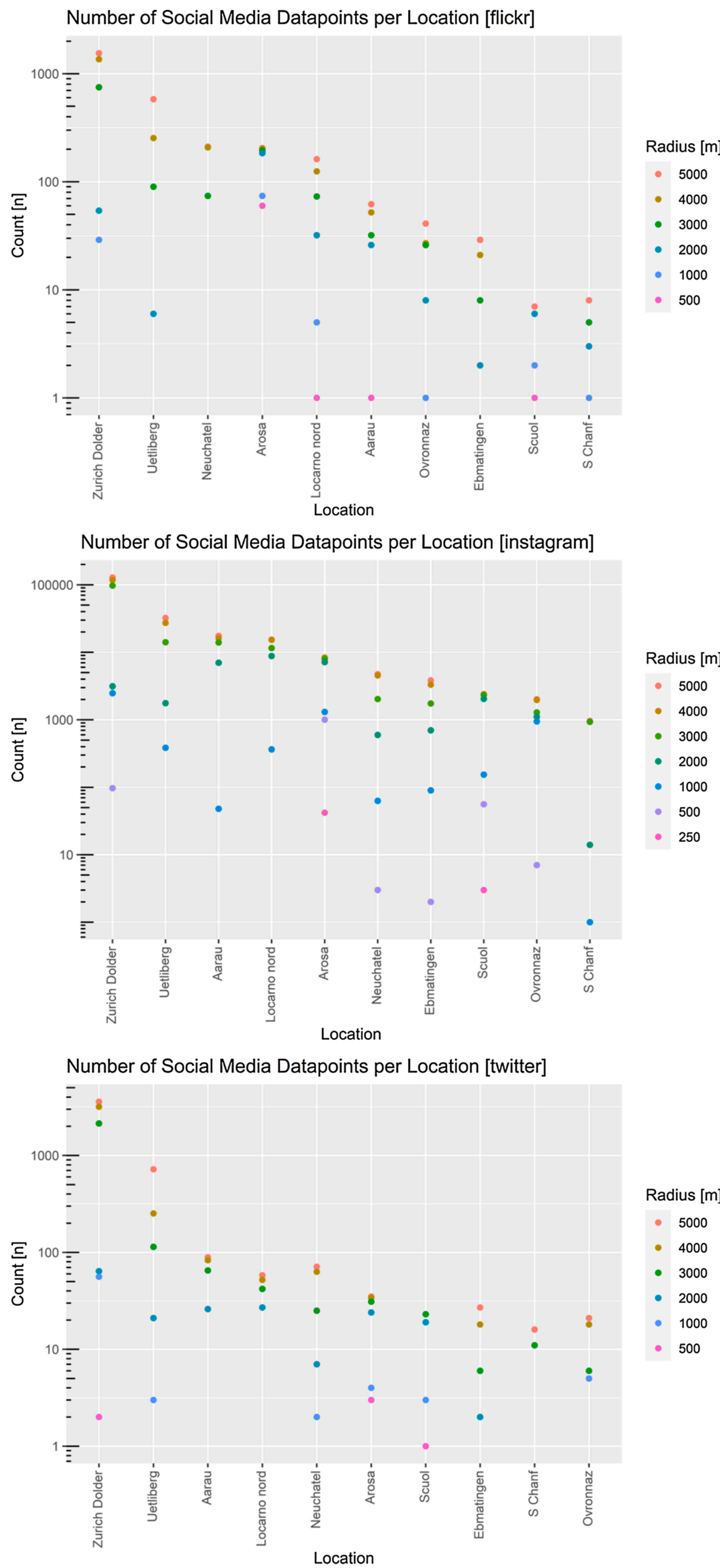

Fig. 2. Data availability around ten selected forest study plots for Flickr, Instagram and Twitter.

0.855; $p < 0.01$)). This result indicates that, depending on the model requirements, we can use data sets with limited absolute numbers of available data to achieve relevant results.

Comparing the different forests from our sample, we conclude that social media data are first and foremost distributed around urban centres and touristically attractive places, such as the city of Zurich, or the alpine destination of Arosa. Less popular alpine locations such as S-chanf had consistently less data across all social media sources.

The spatial assessment of data availability at each plot showed that most social media data are found further away from the plots, typically at the edges of forest areas where paths and hiking trails with good views are often available.

3.2. Analysing textual content of social media data to describe forests

Apart from the location information that can be used to analyse spatial patterns in social media data, in this study we also use the semantic content available in the form of texts associated with the locations of Tweets, Flickr images or Instagram posts. Selecting terms matching lists of terms describing landscapes enabled a semantic analysis that was fast and efficient. In Table 2, the 20 most frequent terms per selected site are displayed. Whereas for Zurich Uetliberg and Locarno, over 100 terms were found that matched our list, which are not all displayed here, at Neuchâtel, we only found 9 terms in total with more than 2 mentions each that matched terms from the list. This may in part be because many tags from Neuchâtel were in French, whereas people tagging in Zurich and Locarno used English terminology (as well as German and/or Italian) for tagging. In Locarno, we found for the category 'elements' terms such as *mountain, forest, trees, leaves*, or *sky*. For the category 'activities' the terms included *hiking, training, racing,* and *training* and 'qualities' included for instance *beautiful, cold, orange.* In Zurich, activities for instance included *cycling, hiking, walking,* and *training,* indicating the popularity of this forest for active recreation of its nearby urban population, matching reality on the ground (Kleiner, 2018).

3.3. Modelling recreation in urban and peri-urban forests based on social media data

We correlated the distance from the closest 10 social media data points with the recreational value of the PRD-model (Brändli and Ulmer, 2001). We found a significant negative relationship between the average distance to the nearest ten Flickr data points (coefficient = −0.865, $p < 0.001$) and the PRD-model, as well as to the nearest ten Twitter data points (coefficient = −0.853, $p < 0.001$). Thus, the models based on social media data show that the closer the next ten social media data points are, the larger the estimated potential recreational use. The residuals from the model show where the models over and underestimate compared to the existing PRD-model. The model based on Flickr data for instance assesses recreational use as higher in areas with lower population density, and lower than the PRD-model in areas with high touristic infrastructure. We hypothesise the difference between the Flickr model and the PRD-model is pronounced in touristic areas, because the PRD-model includes holiday homes in its estimate of population, but most of these inhabited for only part of the year. Flickr on the contrary provides a better estimate of the actual use in areas where the census data is low, but which many people visit, such as the alpine valleys of Switzerland. The patterns of the residuals for both models using Flickr and Twitter data, respectively, show similar patterns. Mapping the residuals highlights that for both models, the residuals were not randomly distributed, but showed strong spatial autocorrelation (Figs. 3 and 4).

In Figs. 3 and 4, the residuals that are close to zero are green. These are areas where the estimates from both the social media model and the PRD-model are close and are mostly in peri-urban and more rural areas of Switzerland's relatively densely populated Central Plateau. The positive residuals are marked in orange and red. These are cells where we estimate the recreational usage to be lower using Flickr data. These locations are mostly found around urban areas such as Zurich, Basel, Geneva, Lausanne and Locarno, where the Flickr estimates are lower, because the PRD-model uses census data on inhabitants, leading to larger estimates than using social media counts. Furthermore, forest usage in these urban areas is dominated by everyday activities (e.g. dog walking, jogging, etc.), which are less likely to be shared using social media than weekend trips or holidays (Hunziker et al., 2012).

Finally, blue cells indicate areas where the Flickr-based model returns higher estimates than the PRD. These are mostly found in less densely populated, but touristically attractive alpine areas. A special case is observed for Flims in Graubünden, where the PRD-model estimates the potential recreational demand higher than the model for forest visitation based on Flickr. This anomaly may be explained by the high number of residential population for Flims (that includes counts of empty holiday homes), but lower social media data counts in this area compared to the estimated population. Interpreting the spatial distribution of residuals thus allows us to discuss the differences between these models in terms of their respective strengths and weaknesses.

However, because the data are spatially autocorrelated, we used a rational quadratic correlation measure to deal with this autocorrelation for our assessment of the correlation between the models. The relationship between distance to nearest social media data points and estimated relationship remains significantly negative (Flickr: $rs = -0.651$, $p < 0.01$; Twitter: $rs = -0.6881$, $p < 0.01$), though the strength of the relationship was somewhat weaker.

While the first analysis assessed forest recreation across Switzerland, subsequently, we focused exclusively on the forest plots. Our analysis of social media data within forest polygons reveals that the correlations are slightly stronger (Flickr: $rs = -0.7011$, $p < 0.01$; Twitter: $rs = -0.7129$, $p < 0.01$). This result indicates that the social media data contained within forests estimates the recreational use slightly closer to the PRD-model than taking into account all social media data. We hypothesise that because the NFI forest polygons do not contain any residential areas, where we would have expected high counts of social media data and consequently high discrepancies between social media data counts and potential recreational demand, the overall correlation slightly increases if such areas are not taken into account. Within forest polygons we find a significant correlation between the two methods, indicating that both Flickr and Twitter produce comparable recreational estimates.

Table 2
Twenty most frequent terms describing landscape elements, qualities or activities.

Zurich Uetliberg		Neuchâtel		Locarno	
term	frequency	term	frequency	term	frequency
winter	11	*beautiful*	4	*autumn*	19
snow	9	*nature*	3	*lake*	15
cars	8	*lake*	3	*view*	12
christmas	7	*tunnel*	3	*snow*	11
autumn	7	*forest*	2	*sun*	11
love	6	*trees*	2	*beautiful*	10
travel	6	*light*	2	*day*	8
trip	5	*autumn*	2	*nature*	8
walking	5	*walk*	2	*happy*	7
nature	5			*trees*	7
sunset	5			*winter*	6
sport	5			*landscape*	6
beautiful	4			*love*	5
day	4			*sunshine*	4
landscape	4			*mountain*	4
beauty	3			*sky*	4
cycling	3			*dog*	4
girl	3			*mountains*	4
morning	3			*sunrise*	4
forest	3			*weekend*	4

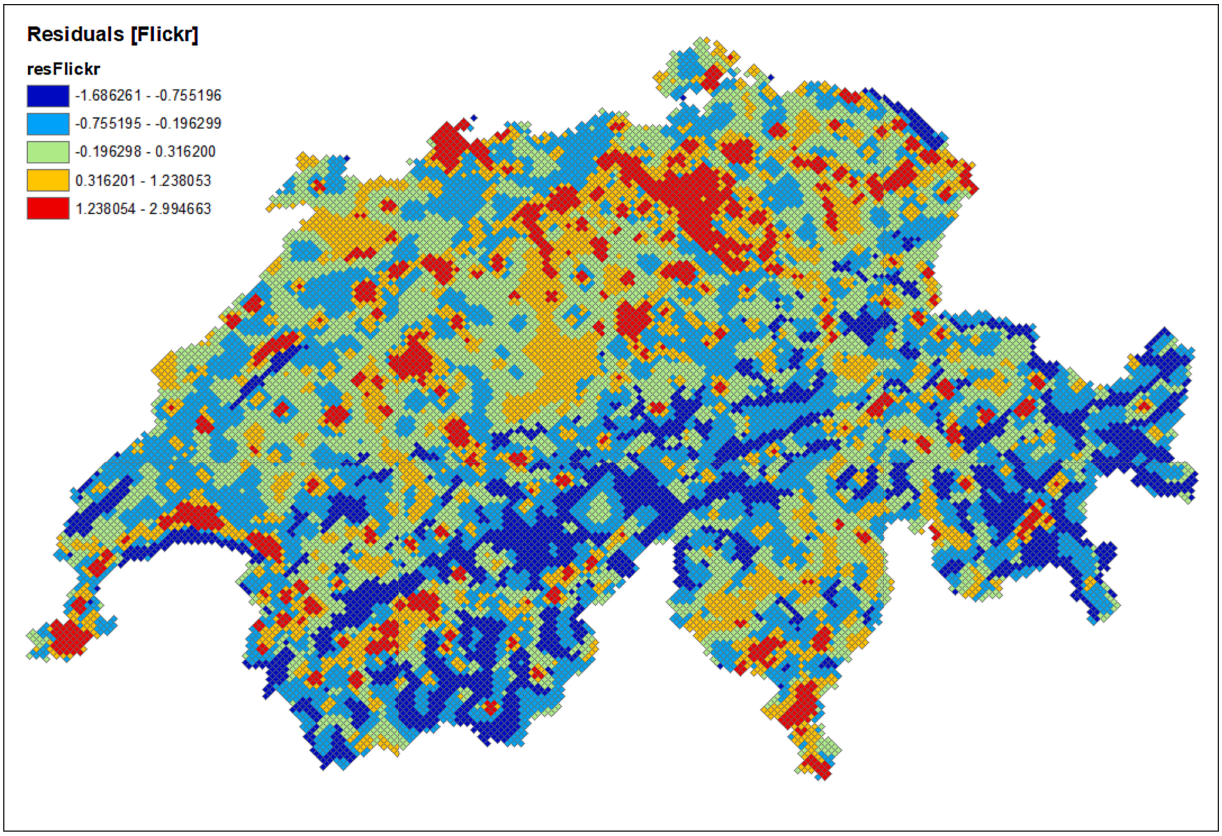

Fig. 3. Residuals for recreational model based on Flickr data (this study) compared to potential recreational demand model (Brändli and Ulmer, 2001).

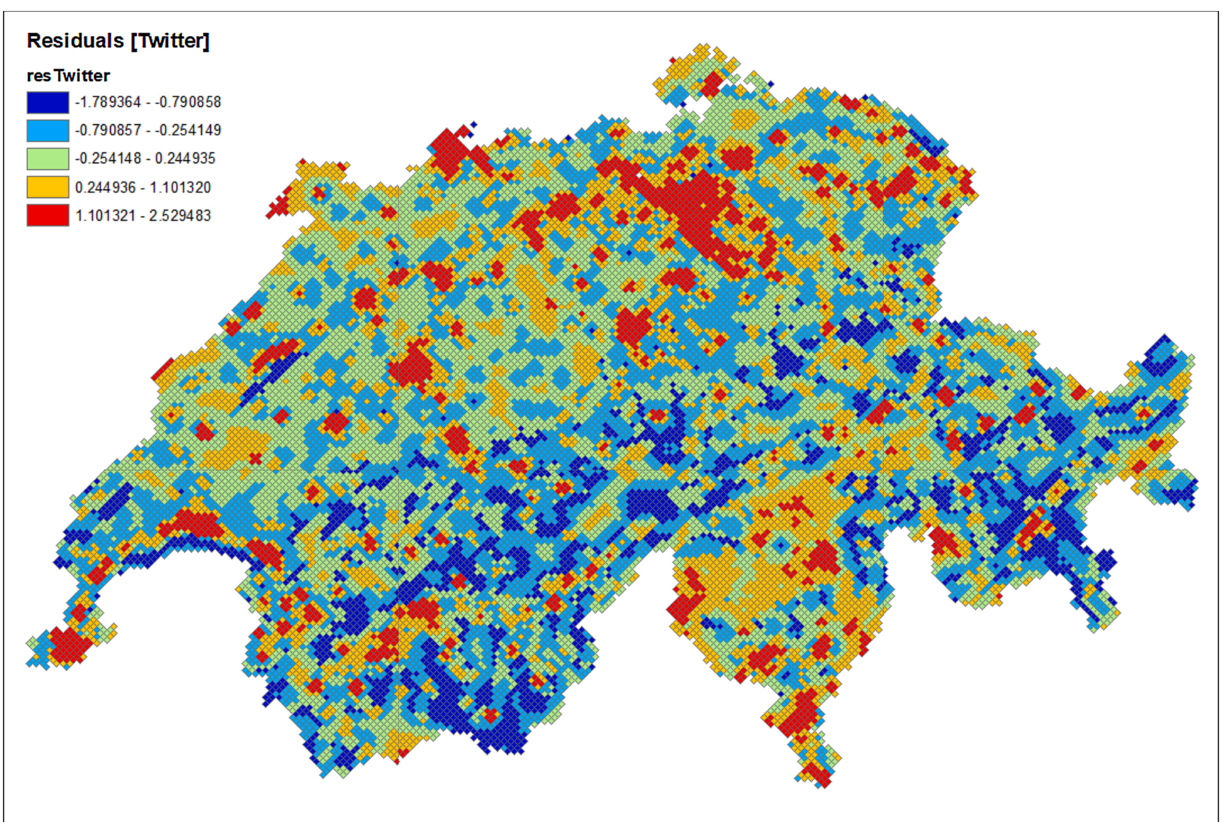

Fig. 4. Residuals for recreational model based on Twitter data (this study) compared to potential recreational demand model (Brändli and Ulmer, 2001).

4. Discussion

The aim of this study was to assess the potential of social media data for assessing recreational uses of urban and peri-urban forests for our case study of forests in Switzerland.

4.1. Availability of social media data in forests

We first compared data availability between different platforms in different forests and found consistent differences. Instagram had by far the most content for our selected forest locations, irrespective of forest site, and datasets were typically orders of magnitudes larger than Twitter and Flickr. However, as all data sources were significantly correlated, we argue that also Flickr and Twitter offer insights into spatial recreation behaviour. Our finding that data availability is significantly correlated between different platforms is in line with previous research that showed similar results for visitors to urban green areas in Minnesota estimated based on Flickr and Twitter (Donahue et al., 2018). Given the large differences between platforms in absolute numbers of social media posts available, we would only compare relative visitation rates using data from the same platform. We note that of the three data sources we used, only Flickr remains available both through an API and with georeferencing as a common feature. One important limitation of our study concerns the period over which we collected data (autumn – early winter). Harvesting data in summer may have changed our results, however.

In response to our first research question, we argue that spatial queries around NFI plots are ill-suited to arrive at conclusive results regarding forest use and perception at small spatial scales. Only a small number of social media posts within a 5000 m radius around our study sites were located within forest, most content was found in nearby urban areas or at forest edges. Even urban forests with known high visitor frequencies such as Uetliberg in Zurich had few social media data located within the forest perimeter itself. In less frequented forests, social media data availability is extremely low. Such low frequencies are very difficult to assess using social media, which we argue are better suited to assess areas of high visitation frequencies, a claim which has been made before for national park areas (Sessions et al., 2016). Furthermore, we hypothesise that the low data availability in forests compared to recreation areas in other landscape types such as urban lakes is related to forests being considered less photogenic than lakes or landscapes with more open views. Preference for open views and water bodies has been theoretically and empirically well demonstrated in environmental psychology (Herzog, 1985; Kaplan and Kaplan, 1989; Orians, 1986; White et al., 2010). The example of the highly frequented Uetliberg forest in Zurich shows, for instance, that many photogenic views (and therefore much social media content) can be found at the edges of the forest with views across the open landscapes. This suggests that for forest recreation research, social media is biased towards forest edges and clearings, as other photographic opportunities within forests are more limited, in turn reducing the social capital that can be gained from uploading content from within forests. This does not mean people do not visit paths and recreational infrastructure within forests, but, again taking the example of Uetliberg forest that sees thousands of visitors each month, it must be assumed that high visitation rates do not always lead to large amounts of social media content. Although previous studies found strong correlations between social media data and on the ground visitor counts for iconic touristic sites (Heikinheimo et al., 2017; Keeler et al., 2015; Sessions et al., 2016), our results indicate that social media data are ill-suited to guide specific management interventions in relatively small, everyday nearby forest recreation areas. This limitation notwithstanding, we suggest that social media data can be used to guide more detailed, on the ground visitor monitoring such as selecting the location for *in situ* visitor surveys or the installation of relatively expensive counting systems such as foot mats or sensors.

4.2. Extracting activities and perceived place-based characteristics from social media data

This brief and explanatory analysis of textual content of social media data from Instagram for three exemplary forest sites highlights that we can rapidly gain insights into activities that are commonly conducted in urban and peri-urban forests. We found that using pre-defined lists of activities from previous research enabled us to quickly process the textual content and find relevant results, for instance hiking and cycling as activities in Zurich's urban forest that match well with a more detailed survey conducted on the ground (Kleiner, 2018). Analysis of such passively crowd-sourced text data enables first results to be gained, e.g. about recreational forest activities at different sites without the necessity for site visits (Wan et al., 2021), or more in-depth studies of mobility data extracted from social media (Norman et al., 2019). For this study, we used pre-defined lists of *activities*, *landscape elements* and *qualities* available in English (Purves et al., 2011). While a lot of social media content in Switzerland is available in English, future work should broaden the analysis to include other languages, for instance by using available analysis of landscape-related terminology from social media data in other languages. While this analysis was exploratory and highlights the potential to use the semantic content from social media data for recreational research, more quantitative analyses are possible that assess similarities between different forests based on natural language analysis of the tags used to describe them.

4.3. Comparing recreational models based on social media with an existing model of potential recreational demand

To assess the potential of social media data to inform models at larger spatial scales, we analysed social media data from Twitter and Flickr across Switzerland and compared a model based on social media data with an existing PRD-model based on census data and accessibility (Brändli and Ulmer, 2001). Our comparison showed that both models (based on Flickr and Twitter data) correlated with the existing PRD-model. This indicates that social media data are a valid source of information for recreational use and can be used in future studies to assess recreational potential. Because the high availability of social media data in urban areas will influence results in urban, built-up areas where recreation potential is low, we calculated a second run of models for forested cells only, and found the correlation between social media models and the PRD-model to become slightly stronger. This indicates that for forests across Switzerland, social media provide a good assessment at large scales. Thus, whereas data availability limits assessments at small spatial scales (Levin et al., 2017), such as for specific small areas of forests, large scale assessments using social media are feasible, and provide a potentially more empirically-grounded assessment of forest recreation than theoretical models for potential demand alone. We suggest that future work should aim at integrating social media data into traditional theoretical recreational models as part of a method triangulation, particularly for alpine areas where recreational usage by visitors is high, but population counts are low.

4.4. Practical implications of limitations in social media data

More and more people are using social media to document their everyday lives and recreational activities. Researchers make use of such data, but questions about the limitations and particularly the representativeness of social media data remain (Tufekci, 2014). It is generally assumed that more educated, younger individuals and people with higher income use social media (Li et al., 2013), but empirical studies have shown that some platforms such as Flickr do not exhibit a bias towards younger people, whereas Twitter and Instagram do (Hausmann et al., 2018). Moreover, the same study provided empirical evidence against the claim that social media is biased towards people with higher income, as people with lower incomes reportedly used more social media (Hausmann et al., 2018). Other studies have shown that groups likely to answer questionnaires often do not use social media (Heikinheimo et al., 2017), indicating that the two methods access two different socio-economic groups and that this data can be combined for a more holistic assessment of landscape perception (Komossa et al., 2020). Particular attention has been paid to the credibility of social media data (Flanagin and Metzger, 2008; Spielman, 2014). For instance for Flickr, the location accuracy and the tagging behaviour were assessed (Hollenstein and Purves, 2010), showing high spatial accuracy of the data and credible tags being used, even though some errors may occur, such as names being incorrectly used because visitors mistake or move boundaries between similar types nearby areas. Thus, when using social media data, it is very important to carefully assess the plausibility of the content with respect to the research question under investigation, as evidenced by Twitter users whose home location was reported as 'from Justin Bieber's heart' (Hecht et al., 2011). These limitations notwithstanding, our research shows that social media data can complement large-scale assessments of potential recreation demand with data on actual visitation, and indicate hotspots of use that require attention. We identified such a hotspot in our social media data for the alpine village of Flims, where the potential recreation demand is low due to low permanent population, but social media data was high. Image content for this area highlights the reason for this hotspot is Caumasee (Fig. 5), a picturesque lake surrounded by forest, which is popularly shared on social media and has been termed an 'Insta-Hype' in local media (Suedostschweiz, 2021).

For forest management considering the recreational function of the forest, estimates of visitor numbers are indespensable. In small defined forest areas, this information can be provided by visitor counting. However, for larger areas it is necessary to rely on models to estimate visitor frequencies. The present study shows that social media data has the potential to be used in combination with other data such as population densities, distance from settlements, expert estimates and GIS-based interview survey data to provide a basis for models estimating use frequencies in large forest areas.

4.5. Outlook and future work

Since this study was conducted access to Instagram data through an API has been removed, Twitter have changed the way in which content is assigned georeferences, and Flickr has considerably reduced the number of images that individuals can store for free. These changes point to dangers for work such as ours using social media, where access is not assured, and changes can to platforms and content can happen overnight.

We suggest that other, non-commercial sources of user-generated content should be increasingly explored, and distinguish between passive and more active ways of crowdsourcing. Examples of passive crowdsourced data include the harvesting of openly available text on the internet through corpus linguistic tools (e.g. Baroni and Bernardini, 2004) or the collaboration with citizen science initiatives that actively collect data of relevance to scientists (but not necessarily collected *for* the benefit of scientists). While citizen science projects have been launched on environmental aspects of forest monitoring (Connors et al., 2012), there is potential for citizen-led projects to generate data that can be used for research on visitor perceptions, and ultimately use. A successful example is the Geograph Britain and Ireland platform (www.geograph.co.uk) that collects landscape images and associated descriptions and which has been used to link perceived qualities of landscapes such as wilderness to physical characteristics (Chang Chien et al., 2020). Launched as a private initiative to obtain images of Britain's landscapes, the site has collected over 6 million images by almost 13,000 contributors. We believe that more research is needed into harvesting and analysing such forms of content generated by users to decrease the dependency on commercial social media platforms that may or may not be available in the long run, and can be run locally or through central organisations involved in forest and landscape monitoring and observation to include public views in addition to expert-based assessments.

Fig. 5. Lake Cauma in Switzerland is an example of a highly photographed forest recreation site on social media (Image credit: M. Baer).

CRediT authorship contribution statement

F.M. Wartmann: Writing - original draft, Writing - review & editing. **M.F. Baer:** Methodology, Software, Formal analysis, Visualization, Writing - review & editing. **K.T. Hegetschweiler:** Writing - review & editing. **C. Fischer:** Data curation, Writing - review & editing. **M. Hunziker:** Conceptualization, Funding acquisition. **R.S. Purves:** Conceptualization, Methodology, Software, Formal analysis, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors report no declarations of interest.

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