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Using crowdsourced images to study selected cultural ecosystem services and their relationships with species richness and carbon sequestration

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Abstract

Due to the difficulty of capturing spatially explicit information on cultural ecosystem services (CES), previous studies have paid less attention to their relationships with other services. In this study, we quantified the relationships between selected CES using crowdsourced photographs, carbon storage and species richness of plants and butterflies for a case study in Saxony, Germany. The relationships were quantified based on the mutual information metric and using principal component analysis. We further conducted a regression analysis to control for environmental and infrastructure factors such as the share of land use classes, landscape diversity and the presence of viewpoints and picnic sites. Our results showed overall positive relationships between CES indicators and carbon sequestration as well as species richness. However, the magnitude of the relationships varied: the CES indicators showed a stronger relationship with butterfly species richness than with plant species richness. Both CES indicators showed the strongest positive relationship with carbon sequestration. This positive relationship was likely driven by forest cover, which was strongly associated with carbon storage. However, our regression analysis also showed that too much forest cover reduces the perceived CES, in particular for landscape aesthetics. Our findings provide additional information for spatial planning in the study region.

Keywords: cultural ecosystem services, crowdsourced photos, mapping ecosystem services, synergies, multifunctional landscape

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1. Introduction

Large areas of Germany are characterized by mosaic landscapes in which forests alternate with urban areas, arable land and grasslands (Bruns et al., 2000; Dittrich et al., 2017). The biodiversity of and the ecosystem services (ES) provided by these mosaic landscapes can be attributed to the individual land use/cover (LULC) classes as well as to the interaction between different classes (Norris et al., 2010; Schaich et al., 2010). Changes in landscape composition are therefore likely to lead to changes in ES provision (Knoke et al., 2016; Steele and Wolz, 2019). For example, an increase in forest cover, as targeted by the German Forest Strategy 2020 (BMELV, 2011) and regional programs of several German federal states (e.g., Sächsisches Staatsministerium, 2013), may involve trade-offs or synergies among different ES. While trade-offs between forest and arable land or grassland are obvious in terms of the resulting food or timber provision, water regulation, and carbon sequestration (e.g. Lautenbach et al., 2017; Locher-Krause et al., 2017), effects of such afforestation programs on other ES categories are less known.

Many intermediate services related to food provisioning - such as crop pollination - require a landscape composition that enables a connection between ES providing and ES demanding areas (Schulp et al., 2014). Likewise, studies have shown that landscape mosaics consisting of forest and agricultural land could be of outmost importance for the provision of cultural ecosystem services (CES) (e.g. van Berkel and Verburg, 2014). However, the relationships between CES and other ES or biodiversity have rarely been studied for landscapes with mixed LULC. As of yet, studies have mostly focused on urban green spaces (e.g., Fuller et al., 2007; Carrus et al., 2015; Southon et al., 2017) or grassland (e.g., Lindemann-Matthies et al., 2010), mostly also for smaller case study extents. For example, Fuller et al. (2007) investigated the psychological benefits of urban green spaces in relationship to species richness. Lindemann-Matthies et al. (2010) studied how species richness of meadow plants affects the aesthetic perception of the landscape.

CES are much more difficult to quantify and map than other ES (Milcu et al., 2013; Chen et al., 2019; Mandle et al., 2020). While 'stated-preferences' methods such as surveys and interviews are most frequently used (Cheng et al., 2019), it remains difficult to convert the information into a spatially explicit representation such as a map. Participatory geographical information systems (PGIS), for example, which allow to determine relationships between human behavior and the environment in a spatially explicit way (Brown et al., 2020; Fagerholm et al., 2021), also heavily rely on 'stated-preferences' methods. These tend to be time-consuming and more difficult to apply on a larger spatial scale (Wood et al., 2013; Havinga et al., 2021). Alternatively, geotagged photographs uploaded to social media platforms (e.g., Flickr, Instagram, Panoramio), showing where people recreate, have been used as a spatially explicit indicator of 'revealed preference' (e.g. Wood et al., 2013; Sonter et al., 2016; van Zanten et al., 2016; Lee et al., 2019; Calcagni et al., 2019). These social media-based studies hence measure beneficiaries' preferences (e.g., for recreational sites or environmental qualities) through direct observation of their behavior (e.g., Pirie, 1976; Adamowicz et al., 1997; Timmins and Murdock, 2007; Jack et al., 2009). One can assume that the more people visit a certain area (1) the higher the attractiveness of the respective landscape (Swaffield et al., 2013) or (2) the easier people can access it due to e.g. infrastructure (Scholte et al., 2015). Both factors might lead to a higher CES value (Gobster et al., 2007; Tribot et al., 2018; Gosal et al., 2021; Havinga et al., 2021). Especially the key factors that determine visitation hotspots (e.g., distance to recreational infrastructure, landscape composition and diversity, and presence of attractive points such as water bodies or certain tourism infrastructure) have been studied using social media data in various contexts (e.g., Tenerelli et al., 2016; van Zanten et al., 2016; Ciesielski and Stereńczak, 2021).

More recent studies have expanded these applications by focusing not only on the geolocation but also on the content of the photographs, making it possible to examine multiple CES (Oteros-Rozas et al., 2018; Lee et al., 2019; Gosal et al., 2019; Egarter Vigl et al., 2021; Väisänen et al., 2021). However, these studies often analyzed CES in isolation with little consideration of relationships with other ES in a multifunctional landscape (Hernández-Morcilloa et al., 2013; Cheng et al., 2019; Lee et al., 2019; Väisänen et al., 2021). As multiple services are spatially distributed in different ways (Castro et al., 2014; Sagebiel et al., 2017), understanding the spatially heterogeneous provision of multiple ES and their relationships, also with biodiversity, is crucial for sustainable landscape management (García-Nieto et al., 2013; Sagebiel et al., 2017). This knowledge gap can hinder the development of management strategies aimed at maintaining the supply of multiple ES and conserving biodiversity (Mori et al., 2016; Albert et al., 2020).

Here, we specifically focused on the opportunities to study relationships between selected CES and regulating services as well as biodiversity indicators using geotagged photographs and their contents in a spatially explicit manner. Like Gosal and Ziv (2020), we here consider geotagged photographs as users' revealed choice of a place to visit and the perceived CES. The case study was conducted in the Mulde basin in Saxony, Germany. The main objective of the 'Forest Strategy 2050 for the Free state of Saxony' is to increase the forest area to 30% of the land (which is still below the German average), mainly to support climate mitigation and to promote multifunctional and more sustainable management (Sächsisches Staatsministerium, 2013, 2021). The LULC change triggered by this initiative is likely to affect biodiversity and multiple ES in different ways including outdoor recreation activities and landscape aesthetics which provide important contributions to the local economy.

Our analysis is based on two previous studies conducted in the Mulde basin, namely mapping of CES by Lee et al. (2019) and modeling of the effects of forest-cover change on carbon sequestration and species richness indicators by Lautenbach et al. (2017). Lee et al. (2019) presented how the perceived CES are spatially distributed and classified photographs based on machine-detected tags into nine clusters, two of which were related to CES uses, namely 'landscape aesthetics' and 'existence'. However, the study did neither consider interactions with other ES nor with environmental or infrastructural conditions. On the other hand, Lautenbach et al. (2017) quantified and mapped the impacts of forest cover change by different afforestation scenarios on carbon storage and plant species richness and analyzed resulting trade-offs.

This present study aims to explore the relationships among the selected CES (i.e., landscpae aesthetics and existence), carbon storage and species richness (plants and butterflies) indicators and finally to explore possible trade-offs and synergies. We aim to paint a more comprehensive picture of the region and support future spatial planning efforts and more informed decision-making. For the study, we have formulated the following hypotheses:

1. Users prefer locations with higher plant and butterfly species richness (synergistic

relationship). We assume that butterflies and insect-pollinated plant species could be of particular importance for users' preference due to their attractive appearance (Lindemann-Matthies et al., 2010; Junge et al., 2015; Graves et al., 2017).

2. A trade-off relationship is assumed between carbon sequestration and the perceived CES since diverse landscapes with higher heterogeneity might be more attractive than dense forest landscapes (Ribe, 1989; Gundersen and Frivold, 2008).
3. Finally, we assume that the spatial distribution of the ES is associated with additional environmental and infrastructural factors (i.e. LULC, landscape diversity and touristic infrastructure) (Ciesielski and Stereńczak, 2021).

2. Materials and methods

2.1. Study area

The Mulde basin is located in the German federal state of Saxony. It covers an area of 5,744 km^2 and is characterized by mosaic landscapes (Figure 1). The largest part of the basin is covered with cropland (53%), which is mostly found on fertile loess and sandy loess soils, followed by forested areas (26%), urban areas (10.2%), and pastures (7%). A large part of the forests in the catchment are coniferous forests with spruce, larch and pine as dominant tree species (Holzwarth et al., 2020). The federal state of Saxony promotes afforestation and designated additional 38.6 km^2 in the basin for afforestation in the regional planning documents (Sächsisches Staatsministerium, 2013). Twelve percent of the Mulde basin have been designated as special protection areas, special areas of conservation or nature reserves in 2012 (Lautenbach et al., 2017). These protected areas are mainly located in the southern mountainous part of the basin. For a more detailed description of the study region see Lautenbach et al. (2017) and Karner et al. (2019).

2.2. Work flow

We divided the work flow into three parts: 1) data preparation for selected ES and biodiversity indicators, 2) analysis of relationships among different ES and species richness, and 3) effects of environmental and infrastructural factors on the spatial distribution of CES (Figure 2). The first step is mainly based on the two previous studies (Lautenbach et al., 2017; Lee et al., 2019). To identify hotspots and quantify relationships among the studied ES in the second step, we used Mutual Information (MI) and principal component analysis (PCA) as widely-used measures of association. The MI analysis quantifies the shared information between two variables, whereas PCA was used for the direction of the relationship and the spatial distribution of PCs. Finally, we tested the effects of environmental and infrastructural factors on the distribution of CES and biodiversity indicators.

2.2.1. Step 1: Data preparation for selected ES and biodiversity indicators

Cultural ecosystem services (CES) indicators. We used the results of the CES mapping conducted by Lee et al. (2019) and closely followed their methodology. As a spatially explicit proxy for the two CES, we used numbers and contents of crowdsourced photographs (cf. Table 1) from the Flickr archive for 2005-2016 in the study area ($n = 12,635$). For each photograph, 20 tags related to the photo contents with their probabilities were assigned using

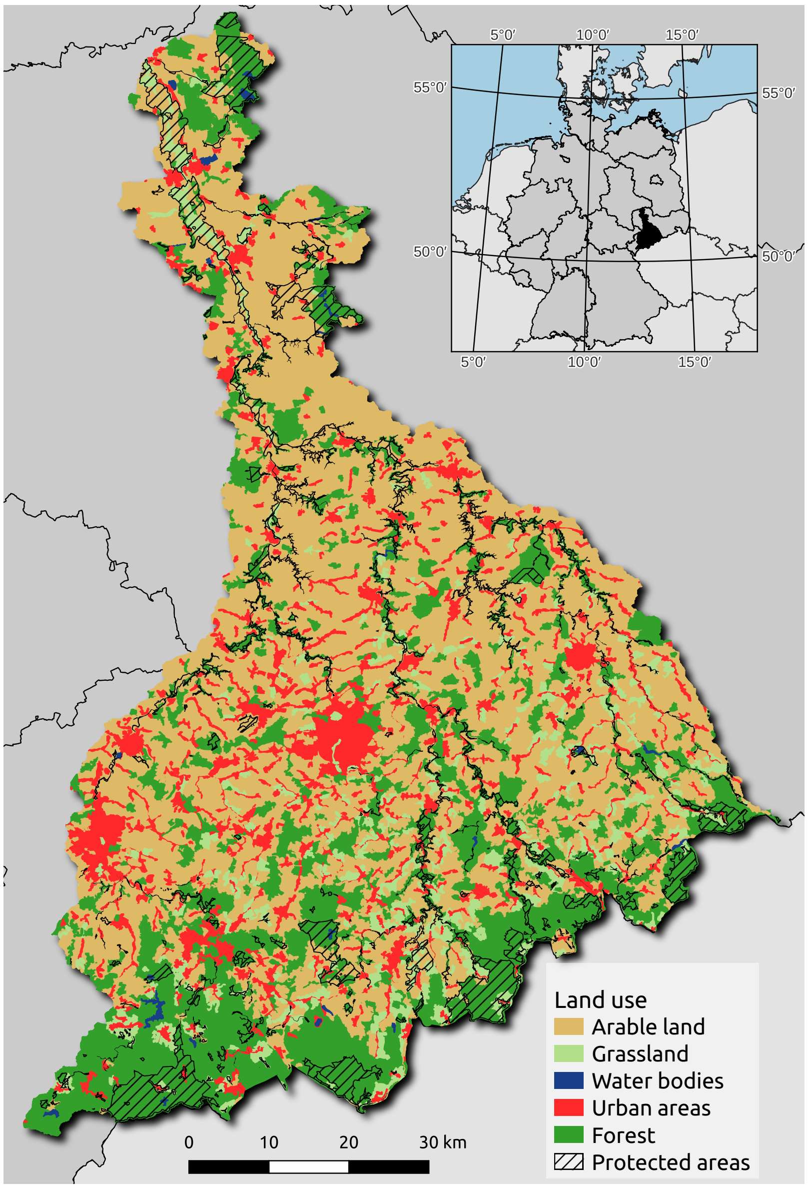

Figure 1: The Mulde basin in Saxony, Germany. Land cover information is based on the 2006 CORINE Land Cover data (CLC2006; Umweltbundesamt, DLR-DFD 2009). Data on protection status (including special protection areas, special areas of conservation, nature reserves, protected landscapes and nature conservation parks) were provided by the Saxonian State Agency for Environment, Agriculture and Geology (LfULG) (LfULG, 2017).

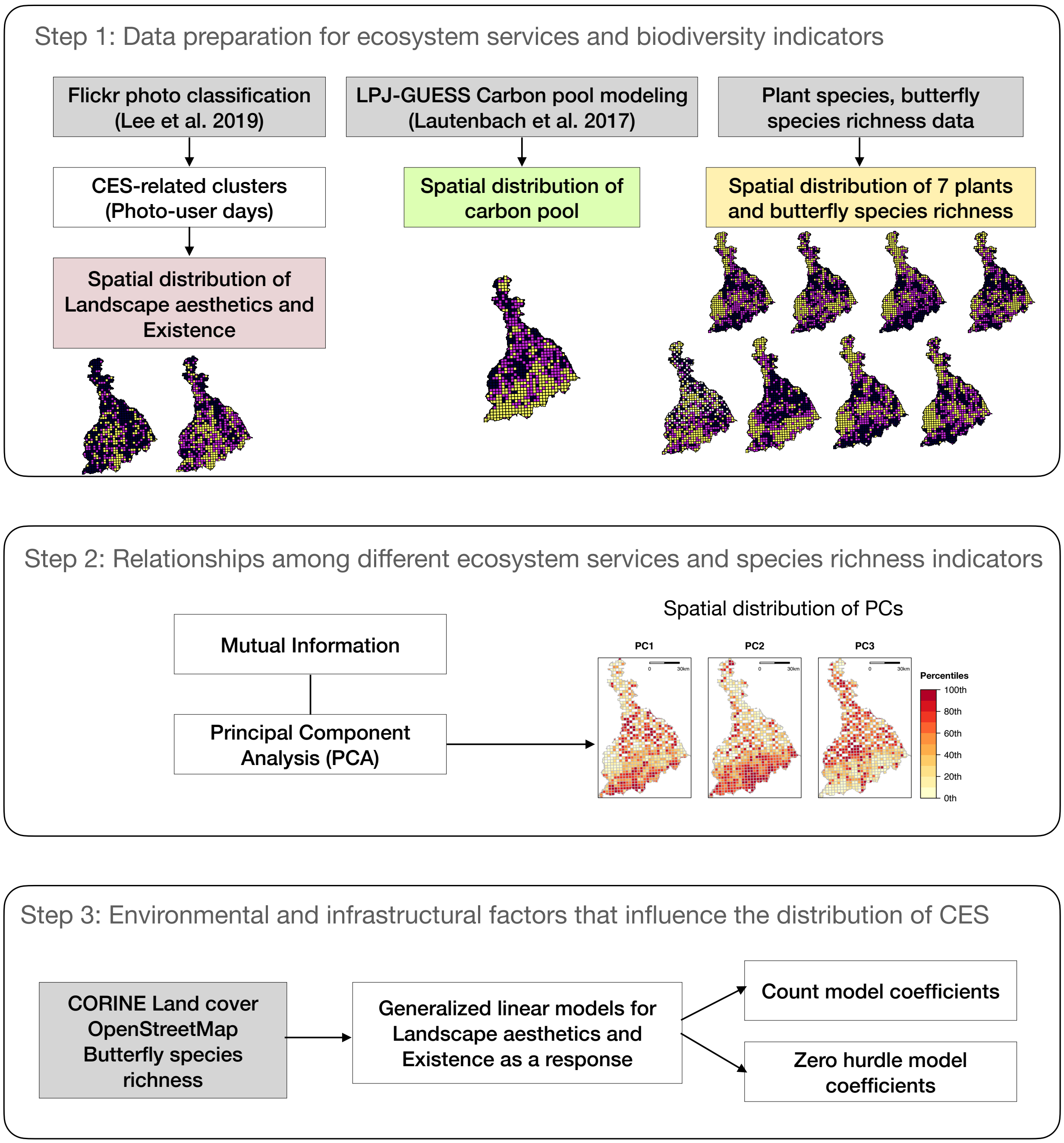

Figure 2: Flowchart of the analysis. Gray boxes indicate input data.

deep Convolutional Neural Networks (CNN) provided at the Clarifai platform[1]. The 2-mode matrix (i.e., 20 tags per photograph) was transformed to a 1-mode matrix based on the co-occurrence information among the 20 tags, which was then used for the tag-network analysis. As in Lee et al. (2019), the theme of the photographs was identified and clustered based on the tag-network using the walktrap algorithm (Pons and Latapy, 2006). This implies that not a single tag, but the combination of the tags was used to determine the theme of the photographs. The photographs were classified into nine clusters, two of which were related to CES classes, namely 'landscape aesthetics' and 'existence'. The 'landscape aesthetics' class was more associated with tags related to the depiction or scenery of landscapes, whereas the 'existence' class was more associated with macro photographs of specific plant and animal species. The full list of tags in each cluster is provided in the Supplementary Material (Supplementary Table ST1). The other identified classes covered activities not related to CES, such as car racing and festivals. In the present study, we only used the photographs classified into the two CES-related clusters (65.1% of the total photos) and associated tags in those photographs. For the detailed procedure of photo content analysis, readers should refer to Lee et al. (2019). We further calculated photo-user-days (PUD) at a 2.8 $\times$ 2.8 km base grid for each CES-related cluster. PUD are defined as the total number of days per year that a photographer took at least one photo within a cell in the study area (Sharp et al., 2016). This approach aims to control for exceptionally high numbers of photographs taken by individual photographers in a specific area on the same day.

Carbon storage modeling. The carbon storage was previously estimated in Lautenbach et al. (2017) using the dynamic vegetation model Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) (Smith et al., 2001, 2011) and a random forest model trained on the vascular flora database of Saxony (Zentrale Artdatenbank (ZenA) Sachsen, 2017b). The LPJ-GUESS model had been run in this study for each combination of soil classes, climatic zones and land use classes (i.e. cropland, forest and pasture). Tree species composition, crop types and agricultural management were adapted to the prevalent conditions in the Mulde basin (Lautenbach et al., 2017). Data on forest structure was derived from a nationwide inventory of forest composition in Germany[2]. Information on dominant crop types were taken from agricultural statistics. Management was adjusted for forests, pasture and cropland inside protected areas. In this analysis, simulated carbon stocks were averaged over the period January 1, 1996 to December 31, 2006. For the detailed description of the result of the carbon stock modeling, readers should refer to Lautenbach et al. (2017). A summary of the indicators used for each ES is given in Table 1.

Biodiversity indicators. Species richness is a fundamental and widely-used indicator of biodiversity (Gotelli and Colwell, 2001; Mace et al., 2012). We used plant and butterfly species richness to compare users' preference for flora and fauna species in this analysis. For plant species richness, we used the database for the study area established in Lautenbach et al. (2017), which is based on the official biodiversity database for Saxony (Zentrale Artdatenbank (ZenA) Sachsen, 2017b). The data used here contains the total number of plant species

[1]wwww.clarifai.com
[2]https://www.wald.sachsen.de/ergebnisse-der-bundeswaldinventur-2-5309.html

(all plants), indigenous species, archaeophytes (i.e., introduced before A.D. 1500), neophytes (i.e., introduced after A.D. 1500), threatened (Red List) species, and species grouped by three pollination traits (i.e., wind-, self-, or insect-pollinated species). All species that belonged to the three categories (critically endangered, endangered or vulnerable) of the "Red List" of plant species in Germany (Korneck et al., 1996) were aggregated to the group of Red List plant species. The butterfly species richness data was derived from the same database (Zentrale Artdatenbank (ZenA) Sachsen, 2017a). All data sets were prepared at a 2.8 × 2.8 km base grid. The total number of pixels was 811.

2.2.2. Step 2: Relationships among different ecosystem services and species richness indicators

Mutual information extraction. Mutual information (MI) is a robust way to quantify relationships between random variables by measuring the information content that is shared (Eq. 1). It can be applied to estimate arbitrary (or non-linear) dependency between the variables (Battiti, 1994).

$$MI(X, Y) = H(X) + H(Y) - H(X, Y), \tag{1}$$

where *H(X)* and *H(Y)* are the Shannon entropy of the random variables, X and Y, respectively, and *H(X, Y)* is the joint Shannon entropy of X and Y (Shannon, 1948). In contrast to the standard Pearson's correlation coefficient, MI can be used for non-linear relationships as it measures the general dependence between two random variables (Battiti, 1994). In comparison to Pearson's correlation coefficient, MI is also less sensitive to outliers (Numata et al., 2008). A comparison with a Pearson correlation analysis is presented in the Supplementary Material (Supplementary Figure SF1).

When the MI is equal to zero, X and Y are independent. The MI metric is non-negative but has no upper bound. To facilitate comparisons between different data sets, the normalized MI proposed by Numata et al. (2008) was used. The normalized MI approaches '1' for increasing mutual information *(X, Y)*, and equals '1' if there is a perfect functional relationship between X and Y. We estimated MI using the R package `infotheo` (Meyer, 2014). The input variables were discretized into N bins ($= N^{1/3}$), where N is the number of samples. To quantify uncertainty, we calculated MI using bootstrap sampling ($n_{boot} = 10,000$) and visualized the resulting distributions. To our knowledge, there are no clear guidelines or thresholds for interpreting MI to determine whether two variables are meaningfully related. Therefore, we normalized MI and primarily compared its relative strength.

Principal Component Analysis (PCA). MI analysis measures the shared information contents between two variables, however, it does not reveal the direction of the relationship, i.e. whether the relationship is synergistic (positive) or a trade-off (negative). We therefore additionally conducted a PCA to investigate the direction of the relationship and the multidimensional patterns in the indicator data. PCA uses an orthogonal transformation to convert observations of possibly correlated variables into a set of values of linearly uncorrelated variables, called principal components (PCs). Since the resulting PCs are ordered in such a way that the first PC has the largest possible variance (i.e., accounts for as much of the variability in the data as possible), the approach is often used to reduce dimensionality by using only the first few and most important PCs (Demšar et al., 2013; Jolliffe and

Cadima, 2016). PCA is sensitive to the relative scaling of the original variables; we therefore z-transformed all indicators prior to the analysis. Pixels with no butterfly data were excluded (n = 158) – all other indicators had no missing values for the 811 pixels and could therefore be used for the analysis. We used only PCs with eigenvalues (λ) > 1 (i.e., Kaiser–Guttman criterion) (Cliff, 1988). For the correlation bi-plots, PC scores were normalized following Gabriel (1971). Small angles between two variables (close to 0°) in the correlation bi-plot indicate a positive correlation. Angles close to 90° indicate that the two variables are not likely to be correlated. Angles close to 180° indicate a negative correlation.

Additionally, we set a threshold to define the direction of the relationship following Lee and Lautenbach (2016). In their review, the relationship between two ES was defined based on the factor loading when multivariate statistics were used. A factor loading over 0.32 referred to a meaningful relationship and the relationship was defined according to the direction of the loading, + and - for a 'synergistic' relationship and a 'trade-off' relationship, respectively. To spatially map the distribution of the hotspots, we mapped the first three principal components separately. All data were reprojected into a 2.8 km base grid in DHDN/Gauss-Kruger zone 4 (EPSG:31468) using a bilinear filter. All calculations were done in R version 3.6.3 (R Core Team, 2020) using the following packages: pscl (Jackman, 2020), sf (Pebesma, 2018) and spdep (Bivand et al., 2013).

2.2.3. Step 3: Environmental and infrastructural factors that influence the distribution of CES

Regression analysis. Since the indicators used for the quantification of the perceived CES were assumed to be associated with additional environmental and infrastructural factors, we performed a regression analysis to control for these factors. The following predictors were used: i) share of the land use classes for forest, grassland, and settlements, ii) presence of viewpoints, iii) presence of picnic sites, iv) number of land use patches, and v) species richness of butterflies and of the different plant groups. We assumed that presence of picnic sites as a proxy for touristic infrastructure would have a positive effect on the number of PUDs for both the 'landscape aesthetics' and the 'existence' clusters and that presence of viewpoints would have a positive effect on the number of PUDs for the 'landscape aesthetics' cluster. We further assumed a positive relationship between species richness and the number of PUDs in the 'existence' cluster and for landscape diversity - measured by the number of patches - and the number of PUDs in the 'landscape aesthetics' cluster. For the share of land use classes, we hypothesized a positive effect of both settlement areas (more visitors due to easier access) and forest/grassland share for PUDs in both clusters. Land use information and number of patches were calculated based on the 2006 CORINE Land cover data set, the presence of viewpoints and picnic sites was extracted from OpenStreetMap using the ohsome API as an interface to the OpenStreetMap History Database (Raifer et al., 2019).

For the analysis, we ran generalized linear models of the negative binomial family with a log link for selected combinations of the predictors. In addition to the main effects, we also tested selected interactions and polynomial effects. The latter were modeled by means of orthogonal polynomials (Gentle, 2009, p. 167) to avoid issues with collinearity. To account for excess zeros in the data, we also ran zero-inflated and hurdle models that combine a binomial process with a truncated count process (Wenger and Freeman, 2008; Zeileis and Jackman, 2008; Zuur et al., 2009). For the description of the count process, we used both a Poisson as well as a negative binomial distribution. The different models were compared based on the AIC (Sakamoto et al., 1986). The presence of spatial autocorrelation was investigated by means of global Moran's I using a neighborhood definition based on the nearest eight neighbors and row-standardized weighting for the creation of the spatial weight matrix.

Both the hurdle and the zero-inflated model family are based on a mixture of two distributions. For the hurdle model, a binomial distribution is used to model the occurrence of non-zero events while a zero-truncated count process is used to model positive counts (Zuur et al., 2009). In contrast, zero-inflated models use a binomial distribution to distinguish between excess zeros and zeros that originate from the count process (Zuur et al., 2009). Similar to the hurdle model, a count process is used to model positive counts. For both approaches, different predictors can be used for the count and the binomial process (Zuur et al., 2009). The predictors were centered and divided by two times the standard deviation which enhances the comparability of the effect sizes of continuous and binary predictors (Gelman and Hill, 2006, p. 57).

3. Results

The MI analysis revealed a varying degree of association between the two CES indicators and carbon storage as well as the species richness indicators (Figure 3). The highest MI of landscape aesthetic was found with the carbon pool (avg. MI = 0.41), followed by butterfly species richness (avg. MI = 0.38) and Red list plant species (avg. MI = 0.35). The 'existence´ indicator showed a similar pattern: the highest MI was found with the carbon pool indicator (avg. MI = 0.32) followed by butterfly species richness (avg. MI = 0.29). This also means that the association between 'existence' and the carbon pool is relatively high followed by the association with butterfly species richness. This information was not clearly revealed in the correlation coefficient analysis (Supplementary figure SF1). Interestingly, Red list plant species richness was much weaker associated with 'existence' than with 'landscape aesthetics' photographs.

The first three components of the PCA, which had eigenvalues >1, explained 78.9% of the variance in the data (Table 2). PC1 (eigenvalue = 6.130), which was negatively correlated with all the plant species richness indicators, explained 51.1% of the total variance. The CES indicators, the butterfly species richness and the carbon pool indicator showed an orthogonal direction to all plant species richness in the bi-plot of PC1 against PC2 (Figure 4, (a) and Table 2), which indicated no correlation. PC2 (eigenvalue = 1.970) explained 16.2% of the variance and the loadings were highest and positive for landscape aesthetics, existence, carbon pool, and butterfly species richness (Table 2). PC3 (eigenvalue = 1.414), which explained 11.1% of the variance, was positively correlated with the existence and landscape aesthetics CES indicators, and negatively correlated with carbon pool and Red list plant species richness.

Overall, the CES values were almost orthogonal to all plant-related indicators except for the Red list species richness indicator which showed a stronger association with the 'landscape aesthetic' photographs.

Figure 5 shows the spatial distributions of the three PCs. Low values of PC1, which reversely represents total plant species richness, were concentrated in western parts of the

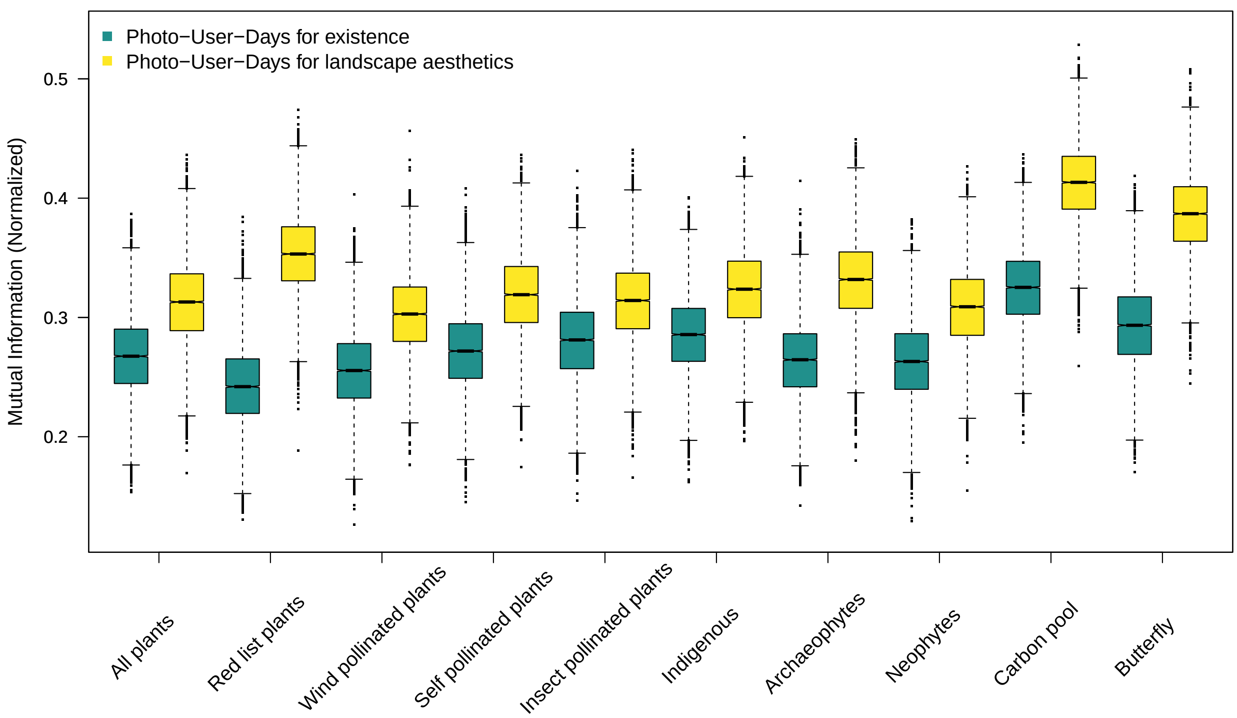

Figure 3: Normalized mutual information (MI) between CES indicators (i.e., photo-user-days of the existence and photo-user-days of landscape aesthetics) and the other biodiversity and ES indicators. The boxplots show the distribution of the estimated MI based on 10,000 bootstrap samples as a robust measure of the uncertainty.

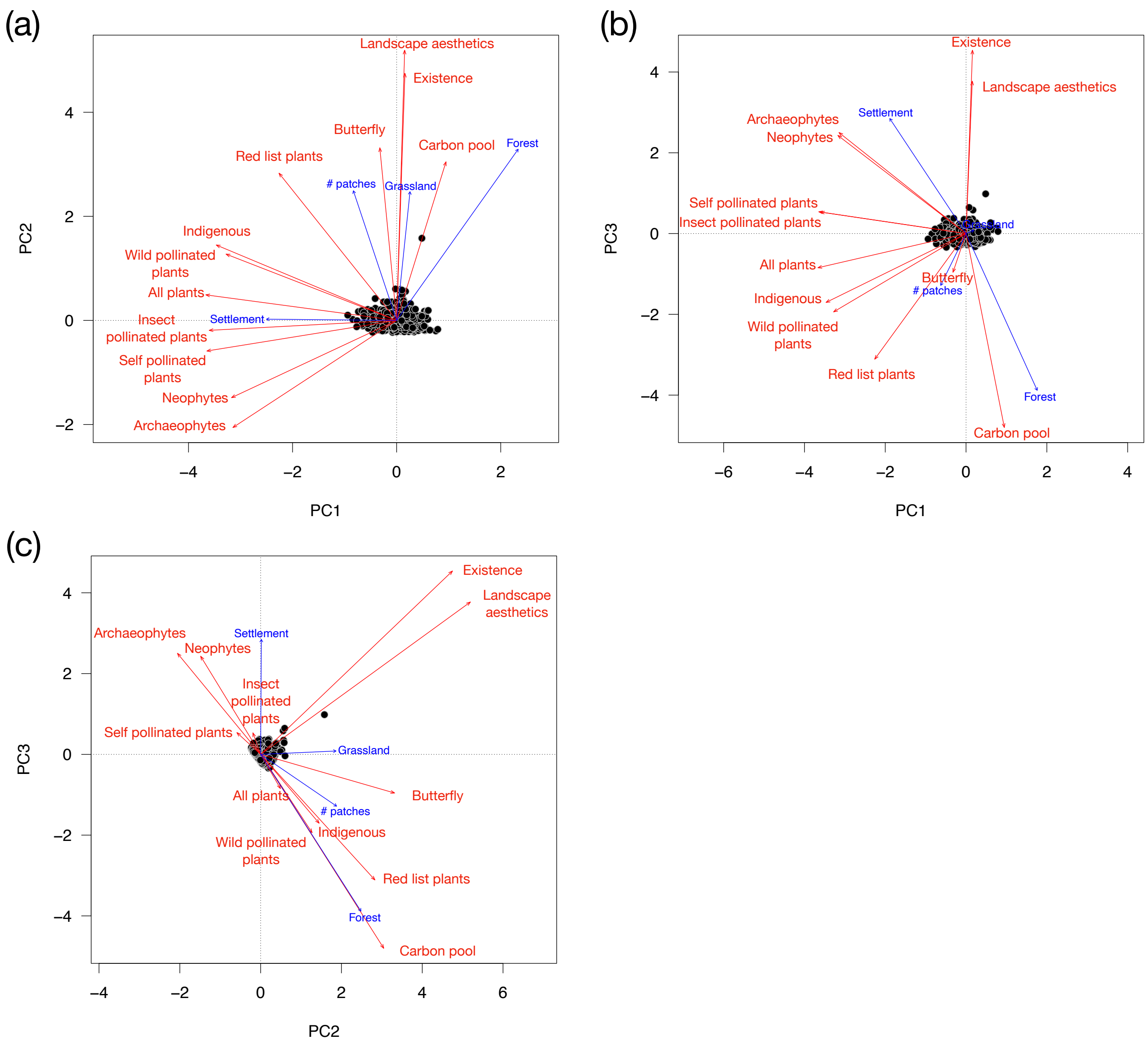

Figure 4: Normalized Principal Component Analysis correlation bi-plots for the input indicators. Arrows represent biodiversity and ES predictors. The direction and the length of the arrows show the correlation between the original variables and the principal components (PC). Three biplots show PC1 and PC2 (a), PC1 and PC3 (b), and PC2 and PC3 (c). Dots represent the 811 raster cells as the tessellation used for the representation of the Mulde basin.

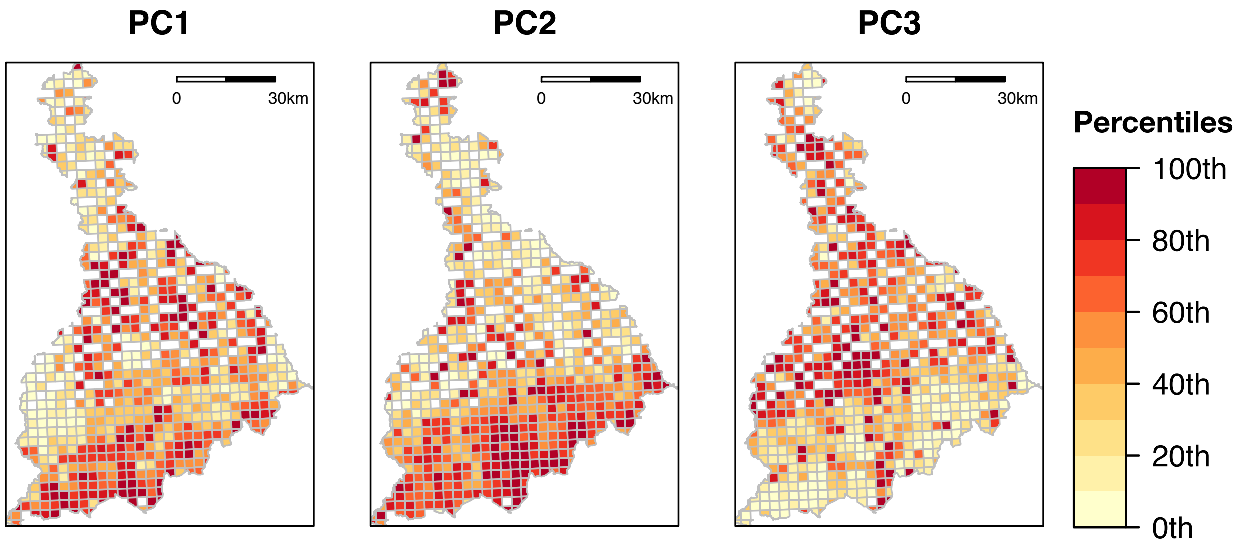

Figure 5: Spatial distributions of the principal components (PCs) with the eigenvalue > 1 in the Mulde basin. White colors represent pixels with no data due to the lack of the butterfly data. Note that the PC values are represented as percentiles to account for the different data ranges.

Mulde basin, whereas the high values of PC2, which represent high indicator values for CES and butterfly species richness, concentrated in the southern area (Figure 5). PC3 spread evenly all over the region, except for the southern areas, which is inversely related to PC2. PC3 was reversely related to the carbon pool indicator. The high carbon pool areas were concentrated in the mainly forested southern areas (Figure 1).

The regression analysis identified a number of significant associations between the number of PUDs and predictors. For both CES, hurdle models with a negative binomial process showed the highest goodness of fit. For the 'landscape aesthetics' photographs, the presence of at least one PUD was higher for grid cells at which picnic sites and/or viewpoints were present (c.f. Table 3). The effect of presence of picnic sites was stronger than for viewpoints. Furthermore, the share of settlement area in the cell and the number of land-use patches in the cell were positively associated with the presence of at least one PUD. For forest share, we found a polynomial effect of second order: the coefficient of the orthogonal polynomial of first order was positive while the coefficient for the polynomial of second order was negative. This implies that the effect of forest share was increasing up to a specific share before decreasing again - the maximum effect of forest share was at around 50%. The effect size of species richness of butterflies was comparable to the effect size of the share of grassland and settlements. Effect sizes for presence of picnic sites and viewpoints were weaker. However, all effect sizes were in the same order of magnitude. The different plant species richness indicators were not or only marginally associated with the CES class 'landscape aesthetics'.

For the 'existence' photographs, the presence of viewpoints was only associated with the presence of at least one PUD but not with the number of PUDs at the grid cell (c.f. Table 4). Presence of picnic sites, butterfly species richness and share of settlements were positively associated with both the presence of at least one PUD and the number of PUDs. The number of PUDs was also positively associated with the share of grassland. Presence of butterflies had the lowest effect size of all predictors, but all effect sizes were in the same order of magnitude. Overall, plant species richness and species richness of insect pollinated plants were only marginally significant in the regression models.

4. Discussion

4.1. Relationships between the perceived CES, carbon storage and biodiversity

The relationship between the two CES considered here, carbon storage and biodiversity is presumably dependent on moderating factors in addition to direct effects. Therefore, associations need to be carefully interpreted. Regarding our first hypothesis, our results showed mixed relationships between the perceived CES and species richness. Both CES indicators were positively related to the species richness of butterflies in the Mulde basin, even if we controlled for confounding factors. The synergistic relationship between 'existence' photographs and butterfly species richness was expected, as the presence of certain species (especially charismatic and endangered species) typically attracts more attention (Gee and Burkhard, 2010; Mace et al., 2012; Milcu et al., 2013) and leads to a higher number of PUDs. This is in line with previous studies that revealed the importance of fauna species - such as birds and butterflies - for people's visit (López-Hoffman et al., 2010; Nahuelhual et al., 2013). This result offers some support for the 'ecosystem services perspective' of biodiversity, which considers biodiversity as an object that humans value directly (Mace et al., 2012, p.21). For the 'landscape aesthetics' photographs, we also identified a positive association with butterfly species richness which was somewhat unexpected. Both CES indicators were highly correlated, so it is reasonable that both were positively associated with butterfly species richness. Interestingly, this association persists, even when controlling for other factors. Even if 'existence' was added to the model for 'landscape aesthetics', a significant positive association with butterfly species richness was found. We assume that the higher landscape diversity, which leads to more diverse habitat conditions but also potentially more attractive landscapes, can explain this relationship.

In contrast to butterfly species richness, a no-effect or a weak relationship between CES and plant species richness was found for both CES indicators. While the total number of photos tagged as containing flowers was much higher (n = 594) than the photos tagged as containing butterflies (n = 135), this did not manifest in a significant relationship between plant species richness and PUDs of the 'existence' photographs. Similarly, Hwang and Roscoe (2017) found that people preferred fauna species over floral diversity for site conservation and maintenance. Among the eight different plant groups considered, self-, insect-pollinated, and indigenous plants showed a relatively but marginally higher level of MI with the 'existence' photographs. However, the PCA revealed that the relationship between plant species richness indicators and both PUD indicators was not clearly directed. This is in line with the regression analysis that did not identify an association.

As for our second hypothesis, we found a positive relationship between the perceived CES and carbon storage, which contradicts our expectations. Although little is known regarding the direct relationship between carbon storage and the different CES (Lee and Lautenbach, 2016), it is crucial to understand whether there is a common driver or a hidden association mechanism among the services (Bennett et al., 2009). In the case of the Mulde basin, the positive relationship between the 'landscape aesthetics' photographs and carbon storage was likely driven by forest cover which was strongly associated with carbon storage. However, results for the 'landscape aesthetics' showed a negative quadratic effect of forest cover which indicates that too much forest cover decreased landscape aesthetics. This result is in line with previous studies (Anderson et al., 2009; Qiu et al., 2013). The results of Qiu et al. (2013), for example, suggest that visitors preferred half-open park areas, which are generally associated with lower carbon storage, over densely vegetated areas.

The spatial patterns revealed in this study might be used as additional information in spatial planning. Higher plant species richness values were concentrated in the western areas of the Mulde basin (Figure 5) where diverse land cover types were found (Figure 1). On the other hand, high CES (i.e. where people prefer to visit), butterfly species richness and carbon storage were located more in the southern areas (Figure 5), in particular in the Ore mountains. The Ore mountains recently became a UNESCO World Heritage Site and attracted over a million overnight-stay travelers in 2019 (Tourismusverband Erzgebirge e.V., 2020). As tourism and people's frequent visits might threaten plant diversity (Pickering and Hill, 2007; Ballantyne and Pickering, 2013; Mason et al., 2015), the current pattern of low rate of overlay between the CES and plant species richness in the Mulde basin could be beneficial to maintain plant diversity since it allows to steer recreation to less sensitive spots. On the other hand, the Ore Mountains (with a long history of mining) contain many small-scale sites of special conservation value (e.g. mining biotopes or rocky ridges resulting from traditional land use practices), which are not necessarily covered by such large-scale analyses as in this study.

4.2. Effects of environmental and infrastructural factors

Additional factors were of importance for the number of PUDs for both CES. Higher landscape diversity - as indicated by the number of patches - presumably leads to a landscape structure which is more appealing to humans as also shown in Hermes et al. (2018) and Oteros-Rozas et al. (2018). While this indicator was only significant for the binomial part of the hurdle model for 'landscape aesthetics', higher shares of forest, grassland and settlement were significant for the count process. Since land use shares add up to 100%, this can be interpreted as an indication of higher landscape diversity. Also, our results of the regression analysis showed that the choice of the location where people visit was influenced by the presence of touristic infrastructure as well as by the presence of nearby settlements, which is in line with previous studies (Hill and Courtney, 2006; Ciesielski and Stereńczak, 2021). Incorporation of such factors should therefore be taken into account for the association between recreation or landscape aesthetics-related indicators with other ES or biodiversity indicators.

Interestingly, forest share showed a quadratic effect: landscapes dominated by forest seemed less attractive for 'landscape aesthetics' photographs than those with a more balanced forest share as mentioned above. The unimodal association between forest cover and the landscape aesthetics indicator affects any linear measure of association such as the Pearson correlation coefficient. The MI approach used here is thus better suited for such non-linear relationships (Dionisio et al., 2004). The PCA assumes linear relationships and is therefore not ideally suited if non-linear relationships are present. The fact that we did not encounter an quadratic effect for grassland share could be related to the lower share of grassland in the region - there were no grid cells dominated by this land cover. For the share of settlements, there might have been two effects: on the one hand the landscape diversity effect as described above, on the other hand the effect of accessibility and the distance to the forest. Hill and Courtney (2006) found that the population living within a 2-hour drive showed a high visitation rate in forested areas. The presence of settlements also implies a higher number of inhabitants seeking recreation, which can link to a higher potential demand for CES (Vallecillo et al., 2019).

4.3. Limitations

Although we here present the potential of social media data to derive relationships between multiple ES, limitations of the approach should be acknowledged. First, the representativeness of social media data is rightly often criticized (Ghermandi and Sinclair, 2019; da Mota and Pickering, 2020). Social media is more actively used by the younger generation, which is typically not representative for all users of a location (Ruths and Pfeffer, 2014; Rossi et al., 2019; Wilkins et al., 2020). Also, we only used one social media platform, Flickr. This potential bias among different social media platforms, however, can be potentially minimized by using multiple sources of social media (Wood et al., 2020) in future work.

Furthermore, machine-learned content analysis can easily and rather quickly reflect what is in the photograph, but not necessarily the motivation for why the picture was taken. This limitation may be addressed by combining crowdsourced photographs with other types of data (Moreno-Llorca et al., 2020). For example, interviews or surveys with users of social media platforms can provide additional information for the interpretation (Stedman et al., 2004; Beckley et al., 2007; Lenormand et al., 2018). In this way, photographers can directly express their preferences and attitude towards specific species, which hence can substantially improve the usefulness of the social-media data. In addition, the analysis of social media posts such as tweets might provide additional insights in the perception of a landscape (Tenkanen et al., 2017).

The analysis of the photo content used in this study did not distinguish between the different plant species – only the general tag ‘flower’ was assigned in the content analysis by the deep neural network. Ongoing developments of machine learning techniques for image recognition will be useful to distinguish different plant species for a more in-depth understanding of the interactive dynamics between human and nature in the future (Horn et al., 2018; Wäldchen and Mäder, 2018).

Finally, the study was conducted at a relatively coarse spatial resolution, based on the available data. We know from other studies that relationships between biodiversity and ES are often scale-dependent. Our results therefore need to be understood in the context of the spatial units studied here and may change in future studies.

5. Conclusion

Overall, relationships between CES indicators, carbon storage and species richness were positive, but to varying degrees. The two CES indicators were not associated with plant species richness, while both CES indicators were positively associated with butterfly species richness. The highest mutual information was found between both CES indicators and carbon sequestration. The regression analysis revealed that it was based on a unimodal relationship between forest cover and the 'landscape aesthetics' indicator. The effect of afforestation on landscape aesthetics will therefore differ depending on the current forest cover extent. Higher carbon storage and therefore higher forest cover was not clearly associated with higher plant species richness which is reasonable as the species included not only forest but also species with other habitat requirements. Based on the spatial analysis results, some locations could be prioritized for a conservation friendly recreation. A tendency for landscapes attractive for recreation to host higher numbers of butterfly species could be either interpreted as a possible win-win situation or as a thread to butterfly diversity as high visitor frequency might have negative effects on biodiversity. Further studies for interactions over time for comparable case study regions are required to investigate this relationship. Developing robust methods for extracting more detailed information on specific species using the applied machine-learning methods and linking this with human behaviors should also be at the core of future research in multifunctional landscapes.

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Conflict of Interest

The authors declare that they have no conflicts of interest.

Ethical statement

The photos from Flickr were analyzed in the study of Lee et al. (2019) in a pseudo-anonymous way, as only an anonymized version of the user ID was used to calculate photo-user-days. A link to the user profile was not established for our analysis. No facial recognition or similar techniques were used in the content analysis of the images by Lee et al. (2019). The analysis for the work presented here only used the aggregated photo-user-day information at the grid-cell level, which should prevent disclosure of Flickr user data.

References

Adamowicz, W., Swait, J., Boxall, P., Louviere, J., Williams, M., 1997. Perceptions versus objective measures of environmental quality in combined revealed and stated preference models of environmental valuation. Journal of environmental economics and management 32, 65–84.

Albert, C., Fürst, C., Ring, I., Sandström, C., 2020. Research note: Spatial planning in europe and central asia – enhancing the consideration of biodiversity and ecosystem services. Landscape and Urban Planning 196, 103741. doi:10.1016/j.landurbplan.2019.103741.

Anderson, B.J., Armsworth, P.R., Eigenbrod, F., Thomas, C.D., Gillings, S., Heinemeyer, A., Roy, D.B., Gaston, K.J., 2009. Spatial covariance between biodiversity and other ecosystem service priorities. Journal of Applied Ecology 46, 888–896. doi:10.1111/j.1365-2664.2009.01666.x.

Ballantyne, M., Pickering, C.M., 2013. Tourism and recreation: a common threat to iucn red-listed vascular plants in europe. Biodiversity and Conservation 22, 3027–3044.

Battiti, R., 1994. Using mutual information for selecting features in supervised neural net learning. IEEE Transactions on Neural Networks 5, 537–550. doi:10.1109/72.298224.

Beckley, T.M., Stedman, R.C., Wallace, S.M., Ambard, M., 2007. Snapshots of what matters most: Using resident- employed photography to articulate attachment to place. Society & Natural Resources 20, 913–929. doi:10.1080/08941920701537007.

Bennett, E.M., Peterson, G.D., Gordon, L.J., 2009. Understanding relationships among multiple ecosystem services. Ecology Letters 12, 1394–1404. doi:10.1111/j.1461-0248.2009.01387.x.

van Berkel, D.B., Verburg, P.H., 2014. Spatial quantification and valuation of cultural ecosystem services in an agricultural landscape. Ecological Indicators 37, 163–174. URL: https://linkinghub.elsevier.com/retrieve/pii/S1470160X1200266X, doi:10.1016/j.ecolind.2012.06.025.

Bivand, R.S., Pebesma, E., Gomez-Rubio, V., 2013. Applied spatial data analysis with R, Second edition. Springer, NY. URL: https://asdar-book.org/.

BMELV, 2011. Forest Strategy 2020. Sustainable Forest Management – An Opportunity and a Challenge for Society. Technical Report. Federal Ministry of Food, Agriculture and Consumer Protection. URL: https://www.bmelv.de/SharedDocs/Downloads/EN/Publications/ForestStrategy2020.pdf;jsessionid=E02AC3AE4BE7D8EC870FAF46EE031A5E.2_cid288?__blob=publicationFile.

Brown, G., Reed, P., Raymond, C.M., 2020. Mapping place values: 10 lessons from two decades of public participation gis empirical research. Applied Geography 116, 102156.

Bruns, D., Ipsen, D., Bohnet, I., 2000. Landscape dynamics in germany. Landscape and Urban Planning 47, 143–158.

Calcagni, F., Maia, A.T.A., Connolly, J.J.T., Langemeyer, J., 2019. Digital co-construction of relational values: understanding the role of social media for sustainability. Sustainability Science , 1–13doi:10.1007/s11625-019-00672-1.

Carrus, G., Scopelliti, M., Lafortezza, R., Colangelo, G., Ferrini, F., Salbitano, F., Agrimi, M., Portoghesi, L., Semenzato, P., Sanesi, G., 2015. Go greener, feel better? the positive effects of biodiversity on the well-being of individuals visiting urban and peri-urban green areas. Landscape and urban planning 134, 221–228.

Castro, A.J., Verburg, P.H., Martín-López, B., Garcia-Llorente, M., Cabello, J., Vaughn, C.C., López, E., 2014. Ecosystem service trade-offs from supply to social demand: A landscape-scale spatial analysis. Landscape and urban Planning 132, 102–110.

Chen, X., de Vries, S., Assmuth, T., Dick, J., Hermans, T., Hertel, O., Jensen, A., Jones, L., Kabisch, S., Lanki, T., et al., 2019. Research challenges for cultural ecosystem services and public health in (peri-) urban environments. Science of the Total Environment 651, 2118–2129.

Cheng, X., Damme, S.V., Li, L., Uyttenhove, P., 2019. Evaluation of cultural ecosystem services: A review of methods. Ecosystem Services 37, 100925. doi:10.1016/j.ecoser.2019.100925.

Ciesielski, M., Stereńczak, K., 2021. Using flickr data and selected environmental characteristics to analyse the temporal and spatial distribution of activities in forest areas. Forest Policy and Economics 129, 102509.

Cliff, N., 1988. The eigenvalues-greater-than-one rule and the reliability of components. Psychological Bulletin 103, 276–279.

da Mota, V.T., Pickering, C., 2020. Using social media to assess nature-based tourism: Current research and future trends. Journal of Outdoor Recreation and Tourism 30, 100295.

Demšar, U., Harris, P., Brunsdon, C., Fotheringham, A.S., McLoone, S., 2013. Principal component analysis on spatial data: an overview. Annals of the Association of American Geographers 103, 106–128.

Dionisio, A., Menezes, R., Mendes, D.A., 2004. Mutual information: a measure of dependency for nonlinear time series. Physica A: Statistical Mechanics and its Applications 344, 326–329.

Dittrich, A., von Wehrden, H., Abson, D.J., Bartkowski, B., Cord, A.F., Fust, P., Hoyer, C., Kambach, S., Meyer, M.A., Radzevičiūtė, R., et al., 2017. Mapping and analysing historical indicators of ecosystem services in germany. Ecological indicators 75, 101–110.

Egarter Vigl, L., Marsoner, T., Giombini, V., Pecher, C., Simion, H., Stemle, E., Tasser, E., Depellegrin, D., 2021. Harnessing artificial intelligence technology and social media data to support Cultural Ecosystem Service assessments. People and Nature n/a. doi:10.1002/pan3.10199.

Fagerholm, N., Raymond, C.M., Olafsson, A.S., Brown, G., Rinne, T., Hasanzadeh, K., Broberg, A., Kyttä, M., 2021. A methodological framework for analysis of participatory mapping data in research, planning, and management. International Journal of Geographical Information Science , 1–28.

Fuller, R.A., Irvine, K.N., Devine-Wright, P., Warren, P.H., Gaston, K.J., 2007. Psychological benefits of greenspace increase with biodiversity. Biology letters 3, 390–394.

Gabriel, K.R., 1971. The biplot graphic display of matrices with application to principal component analysis. Biometrika 58, 453.

García-Nieto, A.P., García-Llorente, M., Iniesta-Arandia, I., Martín-López, B., 2013. Mapping forest ecosystem services: From providing units to beneficiaries. Ecosystem Services 4, 126–138. doi:10.1016/j.ecoser.2013.03.003.

Gee, K., Burkhard, B., 2010. Cultural ecosystem services in the context of offshore wind farming: A case study from the west coast of Schleswig-Holstein. Ecological Complexity 7, 349–358. doi:10.1016/j.ecocom.2010.02.008.

Gelman, A., Hill, J., 2006. Data analysis using regression and multilevel/hierarchical models. Cambridge university press.

Gentle, J.E., 2009. Computational statistics. volume 308. Springer.

Ghermandi, A., Sinclair, M., 2019. Passive crowdsourcing of social media in environmental research: A systematic map. Global environmental change 55, 36–47.

Gobster, P.H., Nassauer, J.I., Daniel, T.C., Fry, G., 2007. The shared landscape: what does aesthetics have to do with ecology? Landscape ecology 22, 959–972.

Gosal, A., Ziv, G., 2020. Landscape aesthetics: Spatial modelling and mapping using social media images and machine learning. Ecological Indicators 117, 106638.

Gosal, A.S., Geijzendorffer, I.R., Václavík, T., Poulin, B., Ziv, G., 2019. Using social media, machine learning and natural language processing to map multiple recreational beneficiaries. Ecosystem Services 38, 100958. doi:10.1016/j.ecoser.2019.100958.

Gosal, A.S., Giannichi, M.L., Beckmann, M., Comber, A., Massenberg, J.R., Palliwoda, J., Roddis, P., Schägner, J.P., Wilson, J., Ziv, G., 2021. Do drivers of nature visitation vary spatially? the importance of context for understanding visitation of nature areas in europe and north america. Science of The Total Environment 776, 145190.

Gotelli, N.J., Colwell, R.K., 2001. Quantifying biodiversity: procedures and pitfalls in the measurement and comparison of species richness. Ecology letters 4, 379–391.

Graves, R.A., Pearson, S.M., Turner, M.G., 2017. Species richness alone does not predict cultural ecosystem service value. Proceedings of the National Academy of Sciences of the United States of America 114, 3774–3779. doi:10.1073/pnas.1701370114.

Gundersen, V.S., Frivold, L.H., 2008. Public preferences for forest structures: A review of quantitative surveys from finland, norway and sweden. Urban Forestry & Urban Greening 7, 241–258.

Haines-Young, R., Potschin, M., 2018. Common International Classification of Ecosystem Services (CICES) V5.1 and Guidance on the Application of the Revised Structure. Technical Report. URL: www.cicies.eu. accessed in March 2019.

Havinga, I., Marcos, D., Bogaart, P.W., Hein, L., Tuia, D., 2021. Social media and deep learning capture the aesthetic quality of the landscape. Scientific Reports 11, 1–11.

Hermes, J., Albert, C., von Haaren, C., 2018. Assessing the aesthetic quality of landscapes in germany. Ecosystem services 31, 296–307.

Hernández-Morcilloa, M., Plieninger, T., Bieling, C., 2013. An empirical review of cultural ecosystem service indicators. Ecological Indicators 29, 434–444. doi:10.1016/j.ecolind.2013.01.013.

Hill, G.W., Courtney, P.R., 2006. Demand analysis projections for recreational visits to countryside woodlands in great britain. Forestry 79, 185–200.

Holzwarth, S., Thonfeld, F., Abdullahi, S., Asam, S., Da Ponte Canova, E., Gessner, U., Huth, J., Kraus, T., Leutner, B., Kuenzer, C., 2020. Earth observation based monitoring of forests in germany: A review. Remote Sensing 12, 3570.

Horn, G.V., Aodha, O.M., Song, Y., Cui, Y., Sun, C., Shepard, A., Adam, H., Perona, P., Belongie, S., 2018. The iNaturalist species classification and detection dataset, in: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 8769–8778.

Hwang, Y.H., Roscoe, C.J., 2017. Preference for site conservation in relation to on-site biodiversity and perceived site attributes: An on-site survey of unmanaged urban greenery in a tropical city. Urban Forestry & Urban Greening 28, 12–20.

Jack, B.K., Leimona, B., Ferraro, P.J., 2009. A revealed preference approach to estimating supply curves for ecosystem services: use of auctions to set payments for soil erosion control in indonesia. Conservation Biology 23, 359–367.

Jackman, S., 2020. pscl: Classes and Methods for R Developed in the Political Science Computational Laboratory. United States Studies Centre, University of Sydney. Sydney, New South Wales, Australia. URL: https://github.com/atahk/pscl/. r package version 1.5.5.

Jolliffe, I.T., Cadima, J., 2016. Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 374, 20150202.

Junge, X., Schüpbach, B., Walter, T., Schmid, B., Lindemann-Matthies, P., 2015. Aesthetic quality of agricultural landscape elements in different seasonal stages in switzerland. Landscape and Urban Planning 133, 67–77. doi:10.1016/j.landurbplan.2014.09.010.

Karner, K., Cord, A.F., Hagemann, N., Hernandez-Mora, N., Holzkämper, A., Jeangros, B., Lienhoop, N., Nitsch, H., Rivas, D., Schmid, E., Schulp, C.J., Strauch, M., van der Zanden, E.H., Volk, M., Willaarts, B., Zarrineh, N., Schönhart, M., 2019. Developing stakeholder-driven scenarios on land sharing and land sparing – insights from five european case studies. Journal of Environmental Management 241, 488–500. doi:10.1016/j.jenvman.2019.03.050.

Knoke, T., Paul, C., Hildebrandt, P., Calvas, B., Castro, L.M., Härtl, F., Döllerer, M., Hamer, U., Windhorst, D., Wiersma, Y.F., et al., 2016. Compositional diversity of rehabilitated tropical lands supports multiple ecosystem services and buffers uncertainties. Nature communications 7, 1–12.

Korneck, D., Schnittler, M., Vollmer, I., 1996. Rote Liste Gefährdeter Pflanzen Deutschlands. Bundesamt für Naturschutz, Bonn. chapter Rote Liste der Farn- und Blütenpflanzen (Pteridophyta et Spermatophyta) Deutschlands. pp. 21–187.

Lautenbach, S., Jungandreas, A., Blanke, J., Lehsten, V., Mühlner, S., Kühn, I., Volk, M., 2017. Trade-offs between plant species richness and carbon storage in the context of afforestation - Examples from afforestation scenarios in the Mulde Basin, Germany. Ecological Indicators 73, 139–155. doi:10.1016/j.ecolind.2016.09.035.

Lee, H., Lautenbach, S., 2016. A quantitative review of relationships between ecosystem services. Ecological Indicators 66, 340–351. doi:10.1016/j.ecolind.2016.02.004.

Lee, H., Seo, B., Koellner, T., Lautenbach, S., 2019. Mapping cultural ecosystem services 2.0 – potential and shortcomings from unlabeled crowd sourced images. Ecological Indicators 96, 505–515. doi:10.1016/j.ecolind.2018.08.035.

Lenormand, M., Luque, S., Langemeyer, J., Tenerelli, P., Zulian, G., Aalders, I., Chivulescu, S., Clemente, P., Dick, J., Van Dijk, J., et al., 2018. Multiscale socio-ecological networks in the age of information. PloS one 13, e0206672.

LfULG, 2017. https://www.natur.sachsen.de/schutzgebiete-in-sachsen-7957.html. Accessed in July 2021.

Lindemann-Matthies, P., Junge, X., Matthies, D., 2010. The influence of plant diversity on people's perception and aesthetic appreciation of grassland vegetation. Biological conservation 143, 195–202.

Locher-Krause, K., Lautenbach, S., Volk, M., 2017. Spatio-temporal change of ecosystem services as a key to understand natural resource utilization in Southern Chile. Regional Environmental Change doi:10.1007/s10113-017-1180-y. publisher: Springer.

López-Hoffman, L., Varady, R.G., Flessa, K.W., Balvanera, P., 2010. Ecosystem services across borders: a framework for transboundary conservation policy. Frontiers in Ecology and the Environment 8, 84–91. doi:10.1890/070216.

Mace, G.M., Norris, K., Fitter, A.H., 2012. Biodiversity and ecosystem services: a multilayered relationship. Trends in Ecology & Evolution 27, 19–26. doi:10.1016/j.tree.2011.08.006.

Mandle, L., Shields-Estrada, A., Chaplin-Kramer, R., Mitchell, M.G.E., Bremer, L.L., Gourevitch, J.D., Hawthorne, P., Johnson, J.A., Robinson, B.E., Smith, J.R., Sonter, L.J., Verutes, G.M., Vogl, A.L., Daily, G.C., Ricketts, T.H., 2020. Increasing decision relevance of ecosystem service science. Nature Sustainability doi:10.1038/s41893-020-00625-y.

Mason, S., Newsome, D., Moore, S., Admiraal, R., 2015. Recreational trampling negatively impacts vegetation structure of an australian biodiversity hotspot. Biodiversity and Conservation 24, 2685–2707.

Meyer, P.E., 2014. infotheo: Information-Theoretic Measures. URL: https://CRAN.R-project.org/package=infotheo. r package version 1.2.0.

Milcu, A.I., Hanspach, J., Abson, D., Fischer, J., 2013. Cultural ecosystem services: A literature review and prospects for future research. Ecology and Society 18, 44. doi:10.5751/ES-05790-180344.

Moreno-Llorca, R., Méndez, P.F., Ros-Candeira, A., Alcaraz-Segura, D., Santamaría, L., Ramos-Ridao, Á.F., Revilla, E., Bonet-García, F.J., Vaz, A.S., 2020. Evaluating tourist profiles and nature-based experiences in biosphere reserves using flickr: Matches and mismatches between online social surveys and photo content analysis. Science of The Total Environment 737, 140067.

Mori, A.S., Lertzman, K.P., Gustafsson, L., 2016. Biodiversity and ecosystem services in forest ecosystems: a research agenda for applied forest ecology. Journal of Applied Ecology 54, 12–27. doi:10.1111/1365-2664.12669.

Nahuelhual, L., Carmona, A., Lozada, P., Jaramillo, A., Aguayo, M., 2013. Mapping recreation and ecotourism as a cultural ecosystem service: An application at the local level in Southern Chile. Applied Geography 40, 71–82. doi:10.1016/j.apgeog.2012.12.004.

Norris, K., Asase, A., Collen, B., Gockowksi, J., Mason, J., Phalan, B., Wade, A., 2010. Biodiversity in a forest-agriculture mosaic–the changing face of west african rainforests. Biological conservation 143, 2341–2350.

Numata, J., Ebenhöh, O., Knapp, E., 2008. Measuring correlations in metabolomic networks with mutual information. Genome Informatics 20, 112–122.

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., Plieninger, T., 2018. Using social media photos to explore the relation between cultural ecosystem services and landscape features across five european sites. Ecological Indicators 94, 74–86.

Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal 10, 439–446. URL: https://doi.org/10.32614/RJ-2018-009, doi:10.32614/RJ-2018-009.

Pickering, C.M., Hill, W., 2007. Impacts of recreation and tourism on plant biodiversity and vegetation in protected areas in australia. Journal of environmental management 85, 791–800.

Pirie, G., 1976. Thoughts on revealed preference and spatial behaviour. Environment and Planning A 8, 947–955.

Pons, P., Latapy, M., 2006. Computing communities in large networks using random walks. Journal of Graph Algorithms and Applications 10, 191–218.

Qiu, L., Lindberg, S., Nielsen, A.B., 2013. Is biodiversity attractive?—on-site perception of recreational and biodiversity values in urban green space. Landscape and Urban Planning 119, 136–146.

R Core Team, 2020. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Vienna, Austria. URL: https://www.R-project.org/.

Raifer, M., Troilo, R., Kowatsch, F., Auer, M., Loos, L., Marx, S., Przybill, K., Fendrich, S., Mocnik, F.B., Zipf, A., 2019. OSHDB: a framework for spatio-temporal analysis of OpenStreetMap history data. Open Geospatial Data, Software and Standards 4, 3. URL: https://opengeospatialdata.springeropen.com/articles/10.1186/s40965-019-0061-3, doi:10.1186/s40965-019-0061-3.

Ribe, R.G., 1989. The aesthetics of forestry: what has empirical preference research taught us? Environmental management 13, 55–74.

Rossi, S.D., Barros, A., Walden-Schreiner, C., Pickering, C., 2019. Using social media images to assess ecosystem services in a remote protected area in the argentinean andes. Ambio , 1–15.

Ruths, D., Pfeffer, J., 2014. Social media for large studies of behavior. Science 346, 1063–1064.

Sächsisches Staatsministerium, 2013. Waldstrategie 2050 für den Freistaat Sachsen. Technical Report. Sächsisches Staatsministerium für Umwelt und Landwirtschaft (SMUL). URL: https://publikationen.sachsen.de/bdb/artikel/11309. accessed in 28 Oct 2021.

Sächsisches Staatsministerium, 2021. Energie- und Klimaprogramm Sachsen 2021. Technical Report. Sächsisches Staatsministerium für Umwelt und Landwirtschaft (SMUL). URL: https://publikationen.sachsen.de/bdb/artikel/37830. accessed in 28 Oct 2021.

Sagebiel, J., Glenk, K., Meyerhoff, J., 2017. Spatially explicit demand for afforestation. Forest Policy and Economics 78, 190–199.

Sakamoto, Y., Ishiguro, M., G., K., 1986. Akaike Information Criterion Statistics. D. Reidel Publishing Company.

Schaich, H., Bieling, C., Plieninger, T., 2010. Linking ecosystem services with cultural landscape research. Gaia-Ecological Perspectives for Science and Society 19, 269–277.

Scholte, S.S., Van Teeffelen, A.J., Verburg, P.H., 2015. Integrating socio-cultural perspectives into ecosystem service valuation: A review of concepts and methods. Ecological economics 114, 67–78.

Schulp, C., Lautenbach, S., Verburg, P., 2014. Quantifying and mapping ecosystem services: Demand and supply of pollination in the European Union. Ecological Indicators 36. doi:10.1016/j.ecolind.2013.07.014.

Shannon, C.E., 1948. A mathematical theory of communication. The Bell System Technical Journal 27, 379–423. doi:10.1002/j.1538-7305.1948.tb01338.x.

Sharp, R., Tallis, H., Ricketts, T., Guerry, A., Wood, S., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E. adn Kennedy, C., Verutes, G., Kim, C., Guannel, G., Papenfus, M., Toft, J., Marsik, M., Bernhardt, J., Griffin, R., Glowinski, K., Chaumont, N., Perelman, A., Lacayo, M., Mandle, L., Hamel, P., Vogl, A., Rogers, L., Bierbower, W., 2016. InVEST+ VERSION + User's Guide. Technical Report. The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund.

Smith, B., Prentice, I.C., Sykes, M.T., 2001. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space. Global Ecology and Biogeography 10, 621–637. doi:10.1046/j.1466-822X.2001.t01-1-00256.x.

Smith, B., Samuelsson, P., Wramneby, A., Rummukainen, M., 2011. A model of the coupled dynamics of climate, vegetation and terrestrial ecosystem biogeochemistry for regional applications. Tellus, Series A: Dynamic Meteorology and Oceanography 63, 87–106. doi:10.1111/j.1600-0870.2010.00477.x. ISBN: 0280-6495.

Sonter, L.J., B.Watson, K., A.Wood, S., Ricketts, T.H., 2016. Spatial and temporal dynamics and value of nature-based recreation, estimated via social media. PLoS ONE 11, e0162372. doi:10.1371/journal.pone.0162372.

Southon, G.E., Jorgensen, A., Dunnett, N., Hoyle, H., Evans, K.L., 2017. Biodiverse perennial meadows have aesthetic value and increase residents' perceptions of site quality in urban green-space. Landscape and Urban Planning 158, 105–118.

Stedman, R., Beckley, T., Wallace, S., Ambard, M., 2004. A picture and 1000 words: Using resident-employed photography to understand attachment to high amenity places. Journal of Leisure Research 36, 580–606.

Steele, M., Wolz, H., 2019. Heterogeneity in the land cover composition and configuration of us cities: implications for ecosystem services. Landscape Ecology 34, 1247–1261.

Swaffield, S.R., McWilliam, W.J., et al., 2013. Landscape aesthetic experience and ecosystem services, in: Dymond, J.R. (Ed.), Ecosystem services in New Zealand–conditions and trends. Mannaki Whenua Press Lincoln, Lincoln, New Zealand. chapter 2.6, pp. 349–362.

Tenerelli, P., Demšar, U., Luque, S., 2016. Crowdsourcing indicators for cultural ecosystem services: A geographically weighted approach for mountain landscapes. Ecological Indicators 64, 237–248. doi:10.1016/j.ecolind.2015.12.042.

Tenkanen, H., Di Minin, E., Heikinheimo, V., Hausmann, A., Herbst, M., Kajala, L., Toivonen, T., 2017. Instagram, flickr, or twitter: Assessing the usability of social media data for visitor monitoring in protected areas. Scientific reports 7, 1–11.

Timmins, C., Murdock, J., 2007. A revealed preference approach to the measurement of congestion in travel cost models. Journal of Environmental Economics and Management 53, 230–249. doi:https://doi.org/10.1016/j.jeem.2006.08.002.

Tourismusverband Erzgebirge e.V., 2020. https://www.erzgebirge-gedachtgemacht.de/news/erzgebirge-erreicht-2019-rekord-der-uebernachtungsbilanz. Accessed in June 2021.

Tribot, A.S., Deter, J., Mouquet, N., 2018. Integrating the aesthetic value of landscapes and biological diversity. Proceedings of the Royal Society B: Biological Sciences 285, 20180971.

Väisänen, T., Heikinheimo, V., Hiippala, T., Toivonen, T., 2021. Exploring human–nature interactions in national parks with social media photographs and computer vision. Conservation Biology 35, 424–436.

Vallecillo, S., La Notte, A., Zulian, G., Ferrini, S., Maes, J., 2019. Ecosystem services accounts: Valuing the actual flow of nature-based recreation from ecosystems to people. Ecological modelling 392, 196–211.

Wäldchen, J., Mäder, P., 2018. Machine learning for image based species identification. Methods in Ecology and Evolution 9, 2216–2225. doi:10.1111/2041-210x.13075.

Wenger, S.J., Freeman, M.C., 2008. Estimating species occurrence, abundance, and detection probability using zero-inflated distributions. Ecology 89, 2953–9. URL: http://www.ncbi.nlm.nih.gov/pubmed/18959332.

Wilkins, E.J., Wood, S.A., Smith, J.W., 2020. Uses and limitations of social media to inform visitor use management in parks and protected areas: A systematic review. Environmental Management , 1–13.

Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. Scientific Reports 3. doi:10.1038/srep02976.

Wood, S.A., Winder, S.G., Lia, E.H., White, E.M., Crowley, C.S., Milnor, A.A., 2020. Next-generation visitation models using social media to estimate recreation on public lands. Scientific reports 10, 1–12.

van Zanten, B.T., van Berkelan, D.B., Meentemeyer, R.K., Smith, J.W., Tieskens, K.F., Verburg, P.H., 2016. Continental-scale quantification of landscape values using social media data. Proceedings of the National Academy of Sciences of the United States of America 113, 12974–12979. doi:10.1073/pnas.1614158113.

Zeileis, AchimKleiber, C., Jackman, S., 2008. Regression models for count data in r. Journal Of Statistical Software 27, 1–25.

Zentrale Artdatenbank (ZenA) Sachsen, 2017a. https://www.natura2000.sachsen.de/schmetterlinge-22624.html. Accessed in July 2021.

Zentrale Artdatenbank (ZenA) Sachsen, 2017b. https://www.natur.sachsen.de/zentrale-artdatenbank-zena-sachsen-6905.html. Accessed in July 2021.

Zuur, A.F., Ieno, E., Walker, N.J., Saveliev, A.A., Smithe, G.M., 2009. Mixed effect models and extensions in ecology with R. Springer. doi:10.1017/CBO9781107415324.004, arXiv:1011.1669v3. ISSN: 1098-6596.

Table 1: Indicators and data for ES and biodiversity used in this study. The description of ecosystem services follows the Common International Classification of Ecosystem Services (CICES) classification scheme version 5.1 (Haines-Young and Potschin, 2018).The biodiversity indicators were divided into two indicators (e.g., plant species and butterfly species richness) representing both flora and fauna.

Ecosystem Services	**Description**	**Indicators**	**Data Source**
Landscape aesthetic	The biophysical characteristics or qualities of species or ecosystems that are appreciated for their inherent beauty	Flickr photos based on photo-contents analysis	Lee et al. (2019)
Existence	The things in nature that we think should be conserved (an existence value)	Flickr photos based on photo-contents analysis	Lee et al. (2019)
Carbon sequestration	Regulation of the concentrations of gases in the atmosphere that impact on global climate or oceans	Calculated by the process-based dynamic vegetation model LPJ-GUESS (Smith et al., 2001)	Lautenbach et al. (2017)
Biodiversity (i.e., maintaining nursery populations and habitats)	The presence of ecological conditions (usually habitats) necessary for sustaining populations of species that people use or enjoy	Plant species richness in 8 different categories: all plants, indigenous, archaeophytes, neophytes, Red List species, wind-, self-, and insect-pollinated species	Zentrale Artdatenbank (ZenA) Sachsen (2017b)
		Butterfly species richness	Zentrale Artdatenbank (ZenA) Sachsen (2017a)

Table 2: Loadings of the first three PCs from the PCA. Explained variance values (%) are shown in parentheses next to PC names.

Indicator	PC1 (51.1%)	PC2 (16.2%)	PC3 (11.1%)
All plants	-0.39	0.06	-0.08
Red list	-0.24	0.31	-0.32
Wind pollinated	-0.35	0.14	-0.20
Self pollinated	-0.39	-0.07	0.05
Insect pollinated	-0.38	-0.02	0.06
Indigenous	-0.37	0.16	-0.17
Archaeophytes	-0.33	-0.24	0.25
Neophytes	-0.34	-0.18	0.24
Carbon pool	0.10	0.35	-0.49
Butterfly	-0.04	0.35	-0.11
Existence	0.01	0.48	0.50
Landscape aesthetics	0.00	0.53	0.44

Table 3: Standardized regression coefficients for hurdle model using the number of PUDs in the 'landscape aesthetics' photographs as the response. Theta represents the shape parameter of the negative binomial distribution and describes the over-/under dispersion of the count process relative to a Poisson process. Regression coefficients are reported at the link scale. Continuous predictors were mean-centered and divided by two standard deviations, such that a one unit change corresponds to a change of one standard deviation below the mean to one standard deviation above the mean. For forest share, an orthogonal polygon of second order was used - effects sizes are therefore not directly comparable among predictors. Share of forest area was strongly associated with carbon storage (MI = 0.78).

	Estimate	Std. Error	z value	p-value
Count model coefficients (truncated negbin with log link):				
Intercept	1.0666	0.1251	8.523	<2e-16
Picnic sites present	0.3885	0.1368	2.841	0.00450
Viewpoints present	0.3326	0.1194	2.785	0.00535
Butterfly species richness	0.5069	0.1242	4.081	4.48e-05
Share grassland	0.5531	0.1108	4.990	6.02e-07
Share settlement	0.5377	0.1234	4.359	1.31e-05
Share forest, polyn. 1th	6.6288	1.7561	3.775	0.00016
Share forest, polyn. 2nd	-4.1015	1.5493	-2.647	0.00811
Log(theta)	-0.3956	0.1503	-2.633	0.00847
Zero hurdle model coefficients (binomial with logit link):				
Intercept	0.4426	0.1430	3.094	0.00197
Picnic sites present	1.0906	0.2066	5.280	1.29e-07
Viewpoints present	0.7357	0.2396	3.070	0.00214
Share settlements	0.7809	0.2778	2.811	0.00493
Number of patches	0.5410	0.2393	2.261	0.02377

Table 4: Regression coefficients for hurdle model using the number of photo user days in the 'existence' photographs as the response. Theta represents the shape parameter of the negative binomial distribution and describes the over-/under dispersion of the count process relative to a Poisson process. Regression coefficient are reported at the link scale. Continuous predictors were mean centered and divided by two standard deviations, such that a one-unit change corresponds to a change of one standard deviation below the mean to one standard deviation above the mean. Share of forest area was strongly associated with carbon storage.

	Estimate	Std. Error	z value	p-value
Count model coefficients (truncated negbin with log link):				
Intercept	-0.5176	0.4052	-1.277	0.201470
Picnic sites present	0.7480	0.2002	3.736	0.000187
Butterfly species richness	0.3781	0.1838	2.057	0.039662
Grassland share	0.5742	0.1812	3.168	0.001533
Settlement share	0.5777	0.1864	3.100	0.001938
Log(theta)	-1.4141	0.5042	-2.804	0.005040
Zero hurdle model coefficients (binomial with logit link):				
Intercept	-0.4664	0.1321	-3.532	0.000413
Picinic sites present	0.6894	0.1744	3.952	7.74e-05
View points present	0.7420	0.1810	4.100	4.13e-05
Butterfly species richness	0.3831	0.1758	2.180	0.029289
Settlement share	0.4643	0.1970	2.357	0.018440