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Continental-scale quantification of landscape values using social media data

Boris T. van Zanten[a,1,2], Derek B. Van Berkel[b,1], Ross K. Meentemeyer[b], Jordan W. Smith[c,d], Koen F. Tieskens[a], and Peter H. Verburg[a]

[a]Environmental Geography Group, Faculty of Earth and Life Sciences, VU University Amsterdam, 1081 HV Amsterdam, The Netherlands; [b]Center for Geospatial Analytics, College of Natural Resources, North Carolina State University, Raleigh, NC 27695; [c]Department of Environment and Society, Utah State University, Logan, UT 84322-5215; and [d]Institute of Outdoor Recreation and Tourism, Utah State University, Logan, UT 84322-5215

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Individuals, communities, and societies ascribe a diverse array of values to landscapes. These values are shaped by the aesthetic, cultural, and recreational benefits and services provided by those landscapes. However, across the globe, processes such as urbanization, agricultural intensification, and abandonment are threatening landscape integrity, altering the personally meaningful connections people have toward specific places. Existing methods used to study landscape values, such as social surveys, are poorly suited to capture dynamic landscape-scale processes across large geographic extents. Social media data, by comparison, can be used to indirectly measure and identify valuable features of landscapes at a regional, continental, and perhaps even worldwide scale. We evaluate the usefulness of different social media platforms—Panoramio, Flickr, and Instagram—and quantify landscape values at a continental scale. We find Panoramio, Flickr, and Instagram data can be used to quantify landscape values, with features of Instagram being especially suitable due to its relatively large population of users and its functional ability of allowing users to attach personally meaningful comments and hashtags to their uploaded images. Although Panoramio, Flickr, and Instagram have different user profiles, our analysis revealed similar patterns of landscape values across Europe across the three platforms. We also found variables describing accessibility, population density, income, mountainous terrain, or proximity to water explained a significant portion of observed variation across data from the different platforms. Social media data can be used to extend our understanding of how and where individuals ascribe value to landscapes across diverse social, political, and ecological boundaries.

cross-cultural analysis | volunteered geolocated content | outdoor recreation and leisure | cultural ecosystem services | European landscape

Individuals, family groups, communities, and entire societies ascribe value and meaning to the landscapes in which they live, work, and play (1). The values and meanings ascribed to landscapes are driven by their aesthetic appeal (2), the recreation and leisure activities they support (3), their social and cultural significance (1), and their ability to improve individuals' mental health and well-being (4). Different methods have been used to evaluate landscape values and meanings, including photo evaluation and illicitation (5), participatory mapping (6), and contingent valuation (7). These data collection techniques are often limited to a small geographic extent, which is unlikely to be representative of values throughout and across societies. Additionally, these methods do not allow for cross-cultural comparison of various landscape values and meanings, which is unfortunate given that many landscapes across the globe are being transformed by similar processes, such as urbanization (8), agricultural intensification (9), and abandonment (10). To date, continent-scale or cross-cultural analyses of landscape values have had to rely on meta-analyses of a very fragmented, diverse, and biased selection of case study locations (11).

Volunteered, publicly available data generated from social media are increasingly being recognized for their potential to answer societally relevant questions in novel ways (12, 13) across large, even global, geographic extents. Social media data can be a transformative tool capable of quantifying landscape values and meanings across large geographic areas. Twitter data, for example, have been used to develop predictive models of the location of natural hazards based on users' awareness of, and "tweets" about, their immediate surroundings (14). Similarly, Facebook data (i.e., posts comprised of text, images, and video) have been used to investigate the geographic spread of social movements (15). The spatial specificity of some social media data, due to the ability to geolocate precisely where content was uploaded, is highly relevant for in situ crowdsourced information (16). In particular, when spatial specificity is combined with volunteer commentary (i.e., captions and hashtags) and other media like photos and video, it can be used to understand how people value and perceive the environment around them (17, 18).

Despite social media's potential for geospatial analyses, only a small set of recent studies have leveraged its capabilities for understanding landscape values (17, 19–21). Data obtained from the photo sharing platform Flickr has been used to identify highly valued recreation and tourism locations (17, 21, 22). Geolocated photos uploaded to Flickr were found to be correlated to actual visitation rates in protected areas with a sufficient level of agreement to warrant the photo sharing website as a good indicator of park visitation rates (17). Another study (20) evaluated keywords

Significance

In many landscapes across the globe, we are witnessing an ongoing functional shift away from landscapes managed for extractive activities (e.g., agriculture, mining, forestry) and toward landscapes managed for recreation and leisure activities. Understanding the spatial configuration of this functional shift at regional and continental scales will be crucial for the development of effective landscape and rural development policies in coming decades. We present a rigorous comparison between three social media platforms' suitability for mapping and quantifying landscape values. We also introduce a predictive model capable of quantifying landscape values at a continental scale. The utility of the model is illustrated through the identification of specific landscape features that best explain high densities of ascribed value (i.e., landscape value locations).

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[1]B.T.v.Z. and D.B.V.B. contributed equally to this work.

[2]To whom correspondence should be addressed. Email: boris.zanten@vu.nl.

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accompanying photos uploaded to both Flickr and Twitter. The textual data provided a more contextually rich understanding of the meanings individuals ascribed to specific locations within the landscape. These types of qualitative data are equally available in the mobile photo sharing application Instagram, which offers users the ability to describe images they share with followers. Despite the research potential offered by social media data (19, 22), there is no empirical evaluation of different social media platforms on their ability to quantify and visualize landscape values.

Europe presents a compelling case study for understanding landscape values given the diversity of the continent's cultural–historical backgrounds and the seemingly strong desire to preserve iconic landscapes (2).* Several studies have attempted to capture locations of significant landscape values across Europe by mapping variables approximating the specific aesthetic value and character of individual regions (23–25). To increase the generalizability of these proxy-based studies, in situ information of landscape values is needed (11, 26). Social media platforms like Panoramio, Instagram, and Flickr, which describe exact locations of where users are enjoying the outdoors and the values they attribute to these location, can potentially add this context-specific in situ information.

The aim of this paper is to explore the potential of geolocated social media content for spatial quantification of the values ascribed to landscapes by individuals enjoying them for aesthetic enjoyment and outdoor recreation. We evaluate the use of web-based photo sharing applications Panoramio and Flickr and the mobile photo sharing application Instagram. Panoramio and Flickr are websites that enable users to upload and display georeferenced photos (19). Members of these sites tend to be photography enthusiasts, with Panoramio users primarily uploading landscape images and Flickr user contributing more diverse subject matter, particularly political and culturally relevant news events. In contrast, Instagram has a broader user base who upload images and descriptive content (i.e., text and hashtags), often real time through mobiles devices. In the United States, 28% of individuals with access to the internet are estimated to be active on Instagram (27). In Europe, estimates vary from 12 million Instagram users in the UK to 6.6 million in France and 8.3 million in Italy (https://napoleoncat.com/blog/en/instagram-user-demographics-in-selected-european-countries/, accessed December 15, 2015).

We interpret spatial concentrations of relevant social media content as indicators of landscape value derived from aesthetic enjoyment and outdoor recreation use. We assume landscape values increase as more people post, photograph, and share information about that landscape. We apply a generalized mixed-effects model (GME) to explain (*i*) the spatial patterns observed in data collected from the three different social media platforms and (*ii*) the specific landscape features that best explain high densities of ascribed value (i.e., highly valued landscapes). We hypothesize that features like topography, proximity to water bodies, and land cover patterns influence landscape values (28–30). We also expect spatial patterns to correlate with regional socioeconomic characteristics (e.g., income) and other context variables, such as the proximity to population centers and accessibility (1, 11).

Results

Collection of social media posts resulted in large numbers of geolocated photos for Panoramio (n = 4,805,933) and Flickr (n = 631,828) representing user contributions uploaded since the launch of these platforms (October 2005 and 2004, respectively). Data-mining constraints imposed by the Instagram application programming interface (API) resulted in a smaller dataset over a shorter period (November 2014–November 2015). Despite these limitations, we obtained 2,094,161 observations. Derived maps of social media posts show broad geographic representativeness for each platform (Fig. 1).

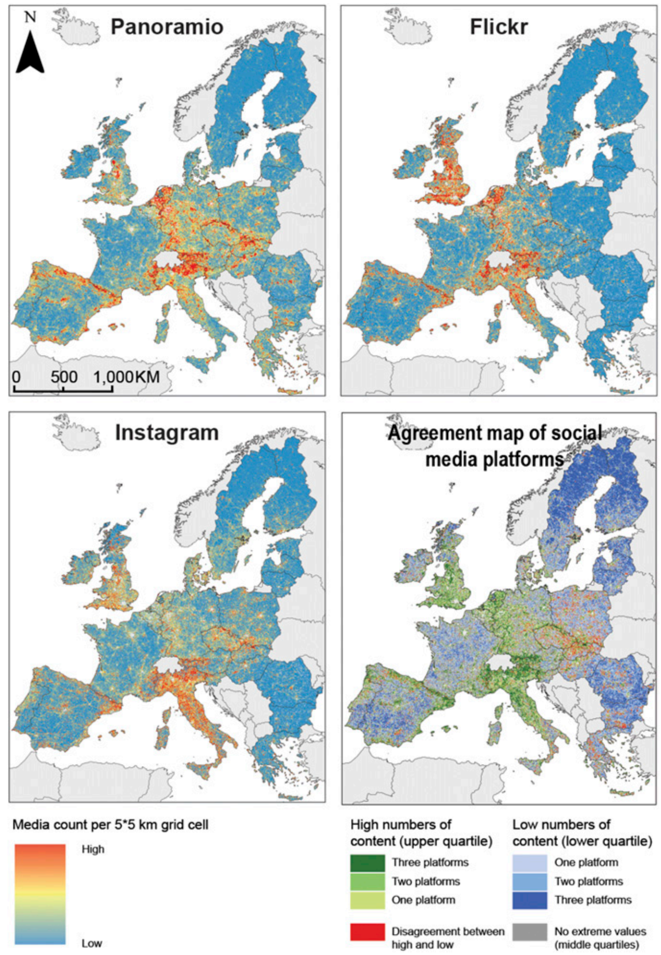

Fig. 1. (*Upper* and *Lower Left*) Stretched values of filtered geolocated content from social media platforms Panoramio, Flickr, and Instagram. All data were mapped and harmonized by aggregating the count of unique user uploads per 1 km^2 at 5 × 5-km resolution. (*Lower Right*) Spatial comparison of social media platforms. Social media layers were reclassified into three values—lower quartile, no extreme value, and upper quartile—and aggregated to estimate areas of like agreement. Maps quantify correspondence between platforms.

Comparison of the Geographic Distribution of Landscape Value Indicators. Our results indicate there is a high level of spatial agreement of geolocated photos obtained through Panoramio, Flickr, and Instagram (Fig. 1). Social media layers were reclassified into three values—lower quartile, no extreme value (middle quartiles), and upper quartile—and aggregated to estimate locations of high spatial correspondence between the platforms (after the method described in ref. 31). Values of 3 (dark green) indicate that content is classified high (dark green, upper quartile) or low (dark blue, lower quartile) over each dataset. No extreme values represent correspondence between platform middle quartiles. We found a mere 6% disagreement between classification of high and low content across the platforms, whereas some areas may not be classified high or low compared with the other social media data (Fig. 2). Spatial agreement is prevalent in mountainous areas, including the

*Council of Europe, The European Landscape Convention, October 20, 2000, Florence, Italy.

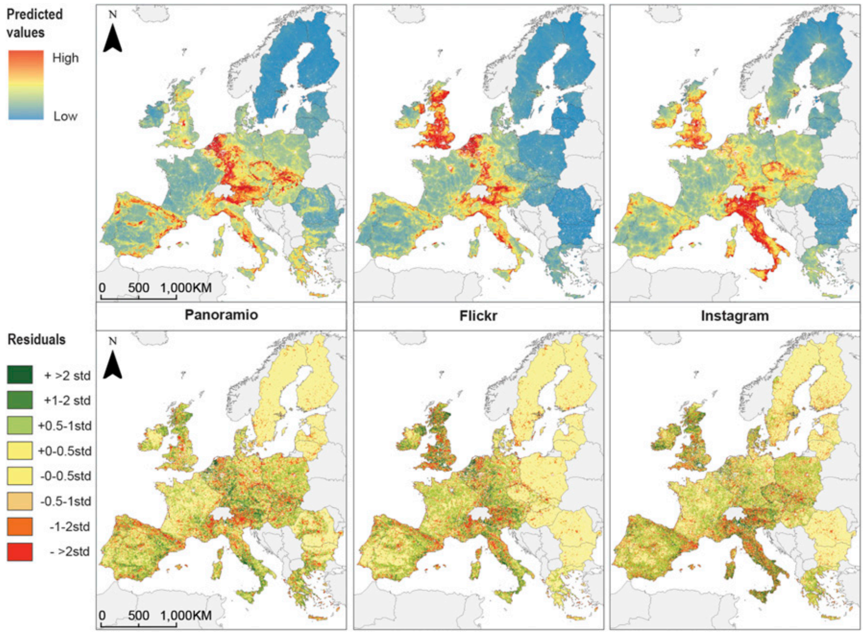

Fig. 2. Residual maps highlight areas where the models over (green pixels) and under (red pixels) estimate aesthetic and outdoor recreation values. All models overestimate values in some mountainous and coastal regions, including areas in northern Scotland and southern Italy between Rome and Naples. As a result of the high intercept values for the United Kingdom, all three models overestimated densities for Scotland and Northern Ireland. Underestimation occurs in the intensively visited mountainous areas of the Alps and Pyrenees as well as at specific sites with highly valued cultural sites (e.g., lower Tuscany, the Lake District in the United Kingdom, the northern wetlands in the Netherlands, and the Camino de Santiago in Spain) that cannot be captured with European-level fixed effects.

Alps, Pyrenees, the Scottish Highlands, and the Apennines. Coastal areas near Cornwall in the UK, Liguria in Italy, and Basque country and the Costa Brava as well as the Balearic Islands in Spain stand out as common presence locations. Absence of photos is prevalent in the agricultural inlands of Spain and France, sparsely populated areas in Nordic and Baltic countries (Sweden, Finland, Estonia, and Latvia), and large parts of Bulgaria and Romania. Areas where there is disagreement across the different platforms are indicated by red pixels (Fig. 1). These areas included the Tatra Mountain range in Slovakia, Czech Republic, and Poland and mountainous areas in Romania, Bulgaria, and Greece. This disagreement is likely caused by the difference in the use of photo sharing applications across Europe. Our results show Instagram and Panoramio are used widely across Europe (Fig. 1), whereas Flickr contributions are largely confined to Central and Western Europe. Although several other studies have used Panoramio and Flickr data independently to quantify the spatial distribution of aesthetic, recreation, and other intangible characteristics (17, 22), a rigorous comparison between Panoramio, Flickr, and Instagram has yet to be performed.

Modeling Landscape Values. We estimate a set of regression models to understand and explain spatial patterns of landscape values. Estimates are based on spatial distributions observed in the count of Panoramio, Flickr, and Instagram geolocated posts describing aesthetic and outdoor recreation values per 5×5-km grid cell as presented in Fig. 1. A landscape's aesthetic and outdoor recreation values are influenced by both landscape features and socioeconomic and cultural characteristics (11). The actual use of landscapes for aesthetic enjoyment and recreation is a result of heterogeneous landscape preferences as well as context variables such as accessibility, infrastructure, and culturally significant protected areas (24, 31). A description of the selection and preparation of the predictors is provided in *SI Appendix*, Table S3.

For each social media platform, we estimate a GME model where the response variables are assumed to follow a Poisson distribution (Table 1). The models' estimates incorporate both fixed-effects parameters and random effects, via maximum likelihood (32), to capture observed variation in social media between countries and likely variation between landscape preferences due to differences in social and cultural preferences (33). Tests of spatial autocorrelation via Moran's I for different lags indicated a significant functional relationship among proximate social media counts and the error terms of model estimates (*SI Appendix*, Fig. S4). To investigate potential spatial autocorrelation bias in estimates, we fit a Poisson model based on eigenvector filtering (34). Eigenvector filtering removes spatial autocorrelation from the residuals of generalized linear models by subsetting spatial data to vectors below a specified alpha value. Comparison of results obtained by fitting the model to both unfiltered and spatially filtered data revealed similar parameter estimates, suggesting our GME results are not biased by spatial autocorrelation. Standardized GME coefficients reveal the relative magnitude of the effects within each model. Goodness of fit was estimated using marginal and conditional R-squared, which allow for assessing the predictive capacity of mixed-effects models (35). Marginal R^2 statistics describe the proportion of variance explained by the fixed factor(s) alone, whereas the conditional R^2 describes the proportion of variance explained by both the fixed and random factors (35). Marginal and conditional R^2 values indicate well-fit estimates for all platforms.

In all three estimations, hills and mountains are the strongest predictors of high aesthetic and outdoor recreation values. Compared with the other landscape features, distance to a water body is a strong predictor in the Instagram model, whereas in the Flickr model the presence of hedges and tree lines has a strong positive effect on the concentration of aesthetic and outdoor recreation values. In all three estimations, an increase of 5-km distance to a city of over 100,000 inhabitants strongly decreases the amount of uploaded content. Additionally, regional

Table 1. GME model estimations for Panoramio, Flickr, and Instagram data

	Panoramio	Flickr	Instagram
Intercept	1.754	-0.335	1.685
Fixed effects			
Landscape features			
Mosaic landscapes, %	−0.001	0.001	−0.005
Hedges and tree lines, count	0.002	0.005	0.014
Proximate to water, cat.	0.003	0.006	0.025
Terrain, rolling, cat.	0.004	0.003	0.004
Terrain, hills, cat.	0.011	0.010	0.035
Terrain, mountains, cat.	0.016	0.015	0.058
Context variables			
Cost–distance to city, h	−0.007	−0.030	−0.064
Protected areas, N2000, cat.	0.004	−0.001	0.018
Distance to PAs, km	0.000	−0.001	−0.001
Peri-urban areas, cat.	0.002	0.004	0.013
Population density p/km^2	0.006	0.005	0.021
Socioeconomic and cultural			
Per capita GDP/1000, NUTS II	0.011	0.017	0.076
Random effects			
N countries	26	26	26
ICC countries	0.094	0.106	0.052
Goodness of fit statistics			
Marginal R^2	0.460	0.357	0.509
Conditional R^2	0.931	0.682	0.861

Model estimates follow a Poisson distribution; variance for counts of the datasets is equal to the mean. Fixed effects are indicated by standardized coefficients. All estimates are significant at $P < 0.01$. Different total of count observations (>0) across the datasets likely influenced the R^2 estimate, making comparison between platforms inadvisable. cat., categorical; GDP, gross domestic product; GME, generalized mixed effects; h, hours; ICC, intraclass correlation coefficient; N, n as in sample size (number of countries); N2000, Natura 2000 (European protected areas); NUTS II, second level of the nomenclature of territorial units for statistics (European classification of regions); p/km^2, per square kilometer; PAs, protected areas (based on N2000 layer).

population density and, to a lesser extent, a categorical variable depicting peri-urban areas are positively related to aesthetic and outdoor recreation values. For the models fit to Panoramio and Instagram data, we found significantly higher photo concentrations in protected areas. Although in both the models fit to Flickr and Instagram data per capita GDP is the strongest positive predictor of photo concentrations, results from the spatially filtered regression results were insignificant, suggesting that GDP is not a strong predictor due to spatial autocorrelation. We accounted for differences in overall use of the social media platforms across countries through the inclusion of a country-level random effect. The intraclass correlation coefficients (ICCs) describe the proportion of the variance of photo concentrations that are explained by the country-level random effects after controlling for all fixed effects. Results indicated there were significant differences in terms of photo concentrations for all platforms across countries. Given this, Flickr data have the largest amount of variance across European countries. Conversely Instagram data were more equally distributed across countries; this also explains the differences in marginal and conditional R^2 values between different datasets.

Predicted values and residuals of the three GME estimations are provided to visualize differences between predicted and observed values for assessing uncertainty associated with model estimates (Fig. 2). For all three platforms, predicted locations with high values depict similar landscape characteristics associated with aesthetic and outdoor recreation values. Higher predicted values are found for mountainous areas, areas near water bodies, and areas near population centers. Variation between countries is visible at the borders between Poland, the Czech Republic, and Germany in the Flickr map, and a bias toward Italy is clear in the Instagram map. Overall, the patterns in the predicted value maps appear to be similar to those presented in Fig. 1.

Discussion

Although social media data have been used to study landscape values, a rigorous comparison between Panoramio, Flickr, and Instagram data has yet to be performed. The platforms have different characteristics affecting both how and how much they are used. The potential strength of Instagram is its relatively large population of users and its functional ability of allowing users to attach personally meaningful comments and hashtags to their uploaded images. Nearly all geolocated Instagram content contains on-site reports (18), a relatively high share of the data examined for this study (30%) describes aesthetic and outdoor recreation values, and our European dataset is relatively equally distributed across European countries (Table 1). Also, we deduce from our comparison of compiled datasets that the Instagram platform has higher user rates relative to the Panoramio and Flickr platforms (36) (https://napoleoncat.com/blog/en/instagram-user-demographics-in-selected-european-countries/, accessed December 15, 2015). These strengths suggest Instagram data could be used to provide a generalizable metric/indicator of landscape values at geographic extents larger than individual sites or landscapes. The potential disadvantage of Instagram data is the limited temporal coverage, which might make it sensitive to bias due to stochastic events such as political upheaval or extreme weather.

The predictive model developed and applied here improves our understanding of spatial relationships between specific landscape features and high densities of aesthetic and outdoor recreation values. Understanding this dependency is of increasing societal relevance, as many areas across the globe are witnessing an ongoing functional shift away from being managed for extractive activities (e.g., agriculture, mining, forestry) toward being managed for recreation and leisure activities (37, 38). At the same time, there are many areas where landscape change is sporadic, characterized by the rapid intensification or abandonment of agriculture. Our spatial analyses suggest the characteristics of specific landscapes (e.g., their accessibility, population densities, mountainous terrain, and their proximity to water bodies) explain a significant amount of observed variation across photo concentrations present in Instagram, Panoramio, and Flickr data (Table 1). However, our continental-scale analysis prevented us from capturing local scale factors that likely influence the aesthetic and recreational enjoyment of the natural environment. Spatial layers representing local attractions, culturally significant locations, and unique environmental features (factors that influence social media posts) could not be included in our analysis due to low data availability and quality. Despite this, we are confident in the generalizability of our results, as similar explanatory variables have been found to be important in other European mapping studies of the quantity and quality of aesthetic and/or outdoor recreation opportunities available to individuals (23, 25). In the absence of socially representative measures of landscape values, such as those that can be derived from social media data, previous research has largely been relegated to using proxy variables describing land use, land management (e.g., protected areas), regional awareness (e.g., certified products), and accessibility. The relative importance of different proxy variables has varied widely, further reinforcing the need for region-, country-, and continental-scale analytical tools.

Questions remain about the social and spatial representativeness of social media data, as the use of different platforms is skewed toward specific demographic groups. Generally, Instagram content is contributed by people between 18 and 29 y of age (27, 37) and has, like other social media, specific limitations based on cultural behavior. Although we have limited information about the demographic characteristics of users in our datasets, the high degree of correspondence between the three platforms, when we take into account country-level random effects, suggests that preference heterogeneity along cultural and/or demographic lines will not drastically change expected locations of aesthetic and outdoor recreation values. Consequently, social media data, particularly data generated through the Instagram platform, can be used to develop indicators of landscape values at scales beyond individual sites or landscapes.

Additional research efforts should address methods that enable a better understanding of the demographic characteristics of social media users and develop improved filtering techniques involving natural language and automatic image processing (37). More research focused in these areas will reduce the technological knowledge and expertise needed to examine social media data for any number of research applications. Additionally, insights into user demographics would identify societal groups that are currently underrepresented (e.g., elderly, ethnic minorities, indigenous people) by social media platforms. Overcoming the challenges provided by social media data and their users could enable the development of a composite indicator of landscape values that integrated data from multiple platforms while controlling for variations in platform use between countries and specific sociodemographic groups.

Materials and Methods

Collecting and Filtering Spatial Social Media Data. We composed three datasets that identify locations of aesthetic and outdoor recreation enjoyment using georeferenced content from Panoramio, Flickr, and Instagram. The data are accessible through APIs (18). The Panoramio dataset contains counts of uploaded photos per unique user per km^2 for nonurban areas. We applied the same measure for Flickr and Instagram data; data from these platforms was collected through the API's location search parameters. Given the specific focus of Panoramio on landscapes and outside locations (22), all content from nonurban origin was included in the dataset. Flickr and Instagram data were keyword-filtered. All content (text and hashtags) was filtered based on matching lists of keywords describing aesthetic and outdoor recreation values in all national languages of the European Union. Downloading and filtering of the social media datasets were done using the Python programming language (libraries Pandas, Textblob, PyProj). For a full description of the preparation of the social media layers, see *SI Appendix, Methods*. Institutional approval and consent was not required for this study.

Data Preparation. The spatial datasets for the predictor variables and the dependent variables (i.e., aesthetic and outdoor recreation values) were aggregated to a 5 × 5-km resolution raster and aligned in ArcGIS. Predictor variables were prepared as follows: Percentage of mosaic landscapes was defined using a focal function around mosaic areas; presence of hedgerows and tree lines is an aggregated version of a 1-km resolution interpolated landscape elements map; areas proximate to water bodies are cells within 10 km of a water body (river, lake, or coast); terrain classes were derived from a 1 km^2 digital elevation model; as an indicator for accessibility, we included cost–distance to the nearest city with >100,000 inhabitants; protected areas were defined as Natura 2000 sites (a harmonized spatial dataset of protected areas throughout the EU); and the distance to protected areas was the Euclidean distance in kilometers to Natura 2000 sites. Peri-urban areas are intermediate density areas in the European degree of urbanization map. We also included an aggregated population density map depicting inhabitants per km^2 and a GDP per capita dataset, which is based on European regional statistics. Finally, urban areas {derived from CORINE landcover data (39)] were excluded from all layers. Elaborate documentation of the selection and preparation of the predictor variables is provided in *SI Appendix*.

Data Analysis. For the presence and absence agreement map, the social media layers were reclassified into three values—lower quartile, no extreme value, and upper quartile—in ArcGIS (31), binning the highest and lowest quartiles of the entire distribution of the sample. Classified images were aggregated estimating total cell agreement across the European Union. Statistical analysis was conducted using R (40). Mixed-effect Poisson models were estimated using the glmer function in the lme4 package (32), whereas Moran's I estimates and eigenvector filtering were conducted using the spdep package (41).

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