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Landscape aesthetics: spatial modelling and mapping using social media images and machine learning

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Declarations of interest: none.

Research highlights:

- Social media images have more aesthetic value than random ones from the same area.
- Probability models can be used to rank-order images for aesthetic value.
- Incomplete paired comparison datasets can be used to rank order of the images.
- Model results were upscaled for 22,615 images and mapped.

Abstract

Cultural ecosystem services such as aesthetic value are highly context-specific and often present difficulties in their assessment. Here we present a case study in the northern English protected area of the Yorkshire Dales National Park. Utilising publicly available images, paired-comparisons survey, machine-learning based text annotations, natural language processing and regression analysis, we developed a spatial model to predict and map landscape aesthetics across the whole site. The predictive model found eighteen significant variables, including the positive role of rural areas, mountains and vegetation for aesthetic value. Finally, we demonstrate the potential of our approach to varying size datasets and partial paired-comparison matrices, finding a very good agreement with only 20% of paired comparisons was found. This study demonstrates the use of freely available data and mostly open source tools to ascertain landscape aesthetic value in a large protected area.

Keywords: Bradley-Terry model, Flickr photos, LUCAS photos, Google Vision, probability models, image content analysis.

Introduction

Landscapes are integral to human welfare and support many human activities, including scientific, education, heritage-based, aesthetic, symbolic, sacred or for entertainment purposes (Haines-Young and Potschin, 2018). These services are integral to human existence, as highlighted by the European Landscape Convention (2000), which recognised their importance for quality of life. Under the Common International Classification of Ecosystem Services (CICES version 5.1), living systems that enable aesthetic experiences are defined as a separate class in the cultural (biotic) service section of the classification (Haines-Young and Potschin, 2018; Oteros-Rozas et al., 2018), providing an aesthetic value to society. The importance of aesthetic services as a cultural service is well accepted, having been enshrined in the Millennium Ecosystem Assessment in 2005 (de Groot and Ramakrishnan, 2005) and the UK National Ecosystem Services Assessment Follow-on reports (Kenter et al., 2014).

Landscape aesthetics has been studied across different disciplines, including psychology, anthropology, evolutionary biology and landscape planning. Whilst this field has grown in socio-ecological research and public interest, it is still missing well developed quantitative and standardised techniques for assessment (Daniel, 2001; Frank et al., 2013; Tenerelli et al., 2017). Biophysical approaches have included spatial modelling (e.g. Dramstad et al., 2006), using stated preference methods such as participatory GIS (Fagerholm and Käyhkö, 2009; Gosal et al., 2018), interviews and questionnaires (Casado-Arzuaga et al., 2013; Kienast et al., 2015), and photographic surveys (Cheng et al., 2019; Palmer, 2004; Schirpke et al., 2013) with numeric Likert scales to allow participants to score photos. Several studies have shown that people aesthetically prefer natural over urban environments (de Groot et al., 2005; Kaplan and Kaplan, 1989).

Gobster et al. (2007) suggests that the history of ancient farming and forestry systems in Europe contribute to the attachment by, and identity of its people, leading to the landscape as being perceived as attractive. Van Zanten et al. (2016) utilised Flickr, Instagram and Panaromio social media photos to quantify aesthetic and recreation values at a continental European scale, finding preference for more mountainous areas. Peña et al. (2015) used aesthetic preference as a proxy for recreation in the Basque Country, Spain, finding mountains and water bodies in landscapes were preferred over homogenous landscapes. Casado-Arzuaga et al. (2014) investigated recreation and aesthetic services in peri-urban environments using a GIS approach finding coastal areas, mountain summits, forests and rural areas corresponded with high aesthetic value. The linkages between ecology and aesthetics have been investigated by Gobster et al. (2007) highlighting that aesthetic experiences are a result of interaction with the 'perceptible realm' (the scale at which humans engage with their landscape surroundings) and are affected by context (landscape or personal-social) . Figueroa-Alfaro and Tang (2017) undertook spatial analysis of geo-tagged photos in Nebraska to identify areas of aesthetic value, and were able to identify clusters of 'new' areas of aesthetic value. Casalegno et al. (2013) quantified online geo-tagged images to evaluate the perceived aesthetic value of an ecosystem finding hotspots of aesthetics value were in coastal areas and a negative correlation with population density. Tenerelli et al. (2017) used social media to investigate the scenic beauty of mountain landscapes in the French Alps, using a technique which combined the images with visual indicators of scenic beauty, with results showing that naturalness, ephemera and visual scale attract foreign visitors, whilst local visits were more attracted by historicity, imageability and complexity. Other studies investigating the features than contribute to aesthetics have included analysis of bundles of landscape features (Oteros-Rozas et al., 2018), within agricultural landscapes (van Zanten et al., 2016b), and Dutch river landscapes (Tieskens et al., 2018).

The usual method of eliciting preference in landscape aesthetics research utilise a Likert scale to rate the images (Hägerhäll et al., 2018; Kaplan and Kaplan, 1989). For example, Masuda et al. (2008) used a Likert scale-based survey to investigate aesthetic preference differences between Americans and East Asians of portrait photos in varying contexts. Seresinhe et al. (2015) demonstrated how crowdsourced ratings for the scenic quality of geotagged photos could be coupled with health data, finding that inhabitants of scenic areas report better health. Research has also shown that social media data combined with OpenStreetMap data (to remove photos taken within buildings) increases the accuracy of scenic quality estimates compared to models using census data alone (Seresinhe et al., 2017a), with the application of neural networks and deep learning allowing extraction of scenic features from images (Seresinhe et al., 2017b).

While being simple to use, the use of Likert scales has known inherent problems. Heine et al. (2002) suggested that cross-cultural comparisons using subjective Likert scales are compromised as they capture a response related to a shared norm, not to the participants' absolute standing. The 'endpoints' of the Likert scale are often set to an individual's expectation of the dimension being measured (Heine et al., 2002; Volkmann, 1951) which varies from one individual to another. Alternatives to the Likert approach are choice experiments and paired comparisons (e.g. Hägerhäll et al. (2018)) to mitigate against the 'endpoints', or internal scale, of the Likert issue.

In a paired-comparison survey, interviewees are faced with two options at each step and are asked to pick the one they prefer. Each comparison is typically done in a second or less. Indeed, literature suggests that people make 'better' choices if they do not engage in conscious thought, with post-choice satisfaction being reduced with introspection (Dijksterhuis and van Olden, 2006) and the greater the number of choices made available (Iyengar and Lepper, 2000). Dijksterhuis and Nordgren (2008) suggest that whereas conscious thought is better for simple decisions, complex decisions are better suited with unconscious thought. Dijksterhuis (2004) suggests that the unconscious thought allows more polarized, clear and integrated representations in memory. Photo paired-comparisons have been used in several studies to understand aesthetics and scenic beauty (DeLucio and Múgica, 1994; Schirpke et al., 2019; Tahvanainen et al., 2001; Tyrväinen et al., 2003). Tyrväinen et al. (2003) used paired-comparisons between images of forests under different management types in. Tahvanainen et al. (2001) examined scenic beauty in Ruissalo Island, Finland, using paired comparison. DeLucio and Múgica (1994) used the paired comparison method to explore landscape preferences from four Spanish national parks. More recently, aesthetic landscape preferences have been investigated by Schirpke et al. (2019) from a paired photo-based survey and other landscape indicators.

In contrast to Likert scale, analysis of paired-comparisons data is slightly more complicated and requires a statistical approach. The Bradley Terry (BT) model is a predictive probability logistic model first studied in the 1920s by (Zermelo, 1929) and later by Bradley and Terry (1952) after whom the model is named. The BT model is built on the concept of 'contests' between two alternatives, be it players, scenarios or images. The model is based on the probability of one item being chosen over another, allowing a full ranking of items to be derived from a sample of paired comparisons (Agresti, 2002; Turner and Firth, 2012; Zucco et al., 2019). The potential for using the BT model with natural landscapes has been highlighted by Hägerhäll et al. (2018) in the field of environmental psychology, who used 9 images, and 36 total comparisons, in a study to investigate human preference for natural landscapes. A second challenge with pair-comparisons data is in upscaling – the number of pair combinations increases as N^2 where N is the number of options (e.g. images). However, there are ways to use the BT model with partial paired-comparison data sets as shown in (Zucco et al., 2019).

Many of the previously mentioned studies used social media data. In their review, Ghermandi and Sinclair (2019) counted 15 studies that used social media to assess aesthetic value of landscapes. Though the use geotagged images and/or photo-user days alone to assess aesthetic value of an area can often be conflated with recreation, making it difficult to understand how much of each service is really being assessed. Innovative approaches have included Lovato et al. (2013) whom attempted to extract aesthetic preference by analysing aspects of Flickr user 'favourite' images, including scenes and colours, which allowed different users to be identified from preference. Yoshimura and Hiura (2017) mapped aesthetic values of landscapes in Hokkaido using social media images and calculation of viewsheds for demand and MaxEnt for supply.

Whereas paired-comparisons based probability models have been previously used in a more limited scope (e.g. Hägerhäll et al. (2018)), here we look at how it can be upscaled across an entire protected area landscape using social media images and machine learning. Our study considers several pertinent issues in the field that guide our research questions:

(a) As the number of paired comparisons increases by a power of 2, how well can this technique be applied to larger datasets with partial coverage and the BT model?

(b) Given that social media photos are likely to be 'aesthetic' (at least to the Flickr user who took and uploaded them), would including publicly available and systematically stratified European Land Use and Coverage Area frame Survey (LUCAS) survey photos (Ballin et al., 2018) give a reference set with a wider 'aesthetic gradient' on which we can train a predictive model?

(c) Can machine learning be used to create a useable set of linguistic predictors for a regression analysis, allowing to extrapolate a BT model based on a subset of images to predict landscape aesthetics at the landscape scale in a given cultural context?

Methods

We adopt multiple techniques, including photo retrieval and content analysis of images using machine-learned APIs and Python scripts, text mining to filter for landscape only images, using natural language processing for synonym term group predictor variables, probability modelling for aesthetic value and finally linear regressions, model selection and mapping. The various steps of the analysis are shown in Figure 1 and explained in detail in the following sections.

Study site

The Yorkshire Dales National Park (YDNP), situated in the north of England (Figure 2) was the site used for this study. The park is known for its natural beauty, with fells over 700m in height, grassy rounded hills with deep ravines, glacial and post-glacial landforms, waterfalls and pastoral landscape (Yorkshire Dales National Park Authority, 2018a). The park is nestled in a highly cultural landscape, with several Areas of Outstanding Natural Beauty (AONB) designated adjacent to the national park including North Pennines AONB, Nidderdale AONB and Forest of Bowland AONB. Designated in 1954, and further expanded in 2016, the YDNP habitats are predominantly enclosed pasture/ grass crop farmland and unenclosed uplands used for grazing (Wilson et al., 2018). The YDNP is seen as a prime example of limestone scenery in the UK, with the largest exposure of Carboniferous limestone in England and having over 30% of English limestone pavements, with three quarters classed as being in good condition (Lee, 2015; Yorkshire Dales National Park Authority, 2018a, 2017). Just under half of the UK's upland calcareous grassland is found in the park, with its blanket bog and upland heathland being important at an international level (Yorkshire Dales National Park Authority, 2017). The park is also home to many important bird species including Curlew, Lapwing and Black Grouse, and provides high-value areas for breeding waders, with important invertebrate species (e.g. the Northern Brown Argus butterfly), Atlantic white-clawed crayfish and mammals including the red squirrel (Wilson et al., 2018; Yorkshire Dales National Park Authority, 2017).

Over 24,000 people work and live in the park (Yorkshire Dales National Park Authority, 2018a). It has been predicted that over the next five years, the resident population in the park will decrease, with a skewed age structure due to younger people moving out of the area (Yorkshire Dales National Park Authority, 2018a). Tourism is important for the national park with 3.85 million visitors (including 0.52 million overnight visitors) totalling 5.06 million tourist days in 2017 alone, bringing in £263 million into the regional economy (Yorkshire Dales National Park Authority, 2018b).

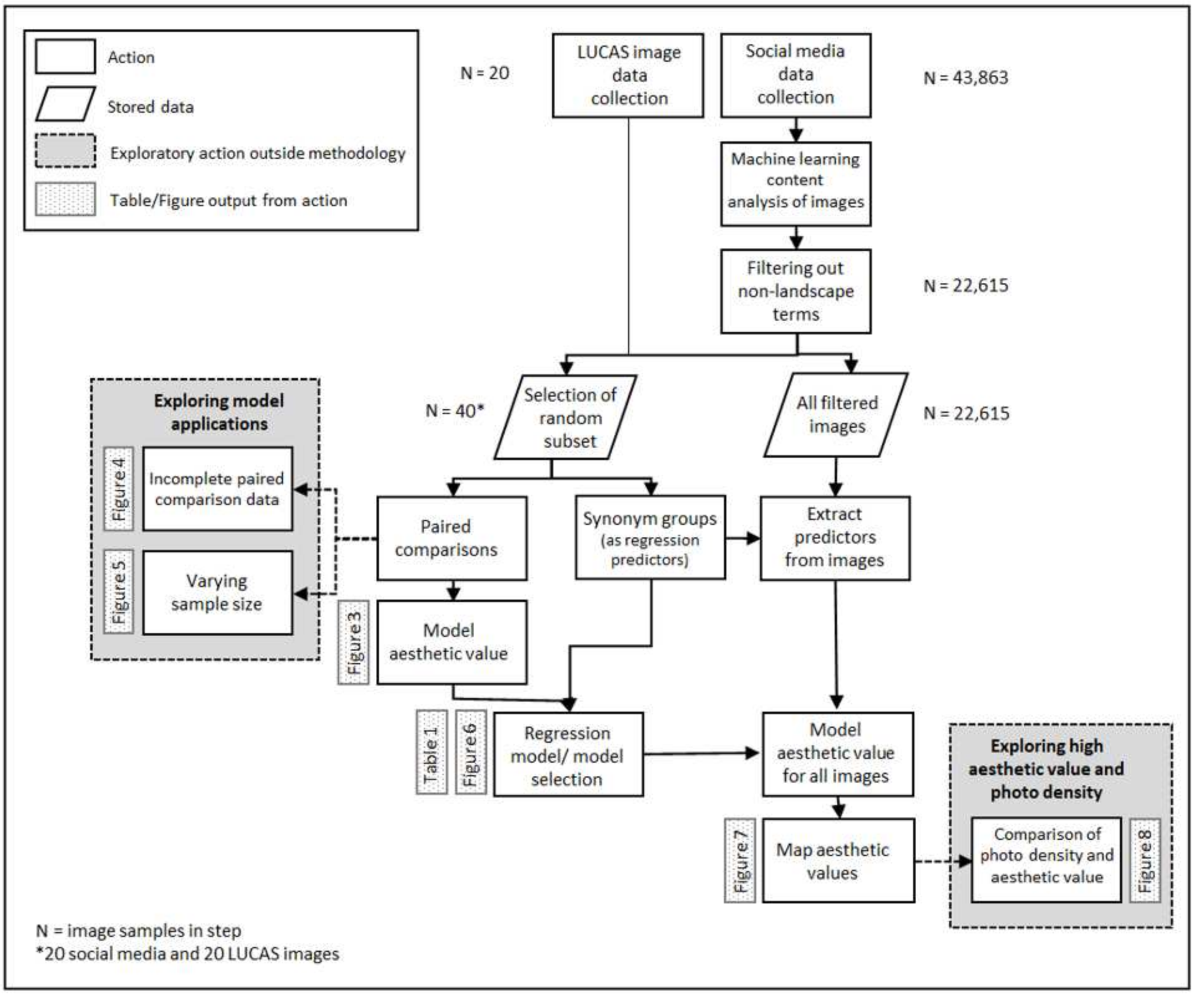

Figure 1. Flow chart of methodology, including additional exploratory processes and relation to table and other figures in this study. The numbers of images (N) at various stages have been included for clarity.

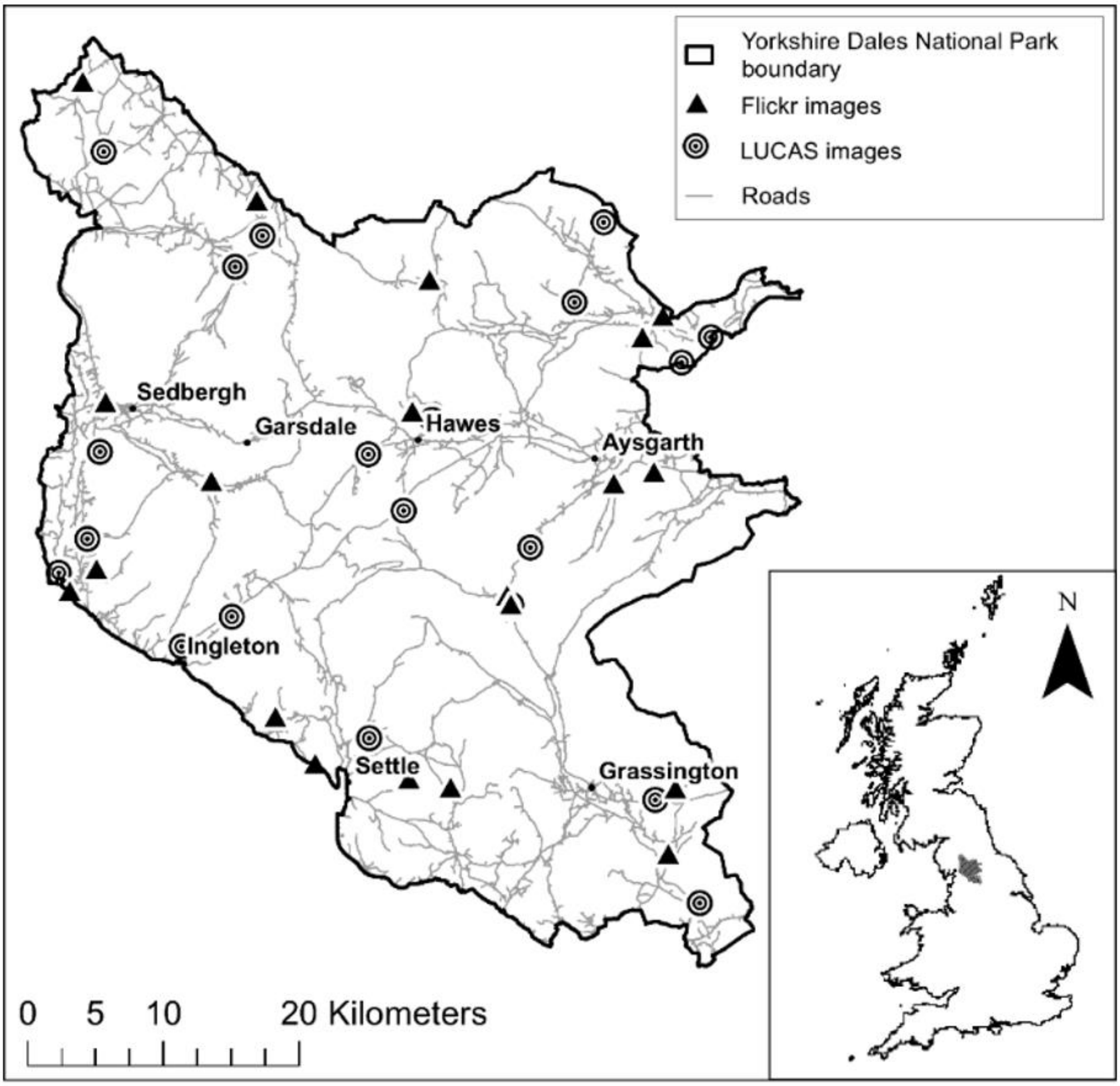

Figure 2. Location of the study site, the Yorkshire Dales National Park, situated in the north of England, with twenty social media (Flickr) and twenty images from the LUCAS database used in this study highlighted. British A and B roads have been included to show proximity to accessible locations. The inset shows the location of the national park within the United Kingdom. © Crown Copyright and database right 2019.

Photo retrieval

Flickr images with associated metadata (including geographic coordinates, date and unique photographic ID) were downloaded for the park with bounding box coordinates and Flickr's Application Programming Interface (API) using the Python 'Scrapy' package. Images were selected for the years 2009-2018 and geographically cropped to the boundary of the Yorkshire Dales National Park resulting in 43,863 images. In addition, we used LUCAS data, which is from points that are sampled from the intersections of a 2 km grid that includes around 1 million points all over the EU (Ballin et al., 2018). Cardinal photos taken by surveyors can be ordered online (Eurostat, 2020). As the location of LUCAS points is pre-determined as a desk-based exercise before field visits, there is no a-priori reason for those photos to be 'beautiful', in contrast to social media photos, which represent the outcome of cognitive decision to take a photo and share it publicly by users. We will hereafter refer to LUCAS points as being 'random' in space, from a landscape aesthetics perspective. Of the combined LUCAS photos surveyed in 2009, 2012 and 2015 (n=302), we randomly kept twenty LUCAS images through a stratified sample using an overlaid 2 by 5 grid (Supplementary material Figure A1).

Content analysis and predictor variables

Images were analysed for content using Google's Cloud Vision API and Python scripts. Google Vision provides labels, hereafter referred to as terms, and confidence scores (between 0 - no confidence and 1 - high confidence) using their pre-trained machine learning algorithm(Google Cloud Vision, 2019), for example, an image may result in being tagged with the term 'highland' with a score of '0.948'. The results were returned as JSON files, which were parsed to extract the terms and scores, above 0.8, in RStudio (RStudio Team, 2015). All terms were manually checked, with 1,393 terms related to human activity or infrastructure, for example, 'terrier', 'garden gnome', or 'coffee house', used to filter the images, resulting in 22,615 images related to landscape with minimal human infrastructure. The term 'farm' was kept, as though it is related to human infrastructure, the UK landscape is heavily influenced with a history of farming which has shaped our landscapes. The final set of photos in predominantly natural landscape type images. Of these, twenty images were selected at random for the paired-comparisons survey (Supplementary material Table A1).

Techniques from text mining were used to create a term-document matrix of all terms from all forty images (twenty each from Flickr and LUCAS) using the 'tm' R package (Feinerer et al., 2008; Feinerer and Hornik, 2018), with infrequent partial terms greater than a threshold of 0.95 removed, resulting in 36 terms (such as 'plant', 'highland' and 'stream'). These remaining terms were passed into 'Wordnet' lexical English database, where words are grouped by sets of cognitive synonyms, using the 'wordnet' R package for nouns and verbs, and the synonyms for each term extracted (Feinerer and Hornik, 2017; Fellbaum, 1998). The resulting term synonym groups (e.g. highland had 'highland' and 'upland') were used to filter terms for all images (all landscape filtered Flicker images and LUCAS images), and dummy variables created, allocating '0' for non-presence and '1' for presence of the term synonym group. The term synonym groups 'grass' and 'pasture' were removed, as all images had presence of these groups, resulting in 34 dummy variables which were later used as predictors.

Paired-comparison survey

An online experiment interface was built using Construct 3 (Scirra Ltd, 2019), a system designed predominantly as a game editor. The experiment was designed to present in a random order all paired comparisons (780 in total for 40 images), with the user asked to choose the image they found most aesthetically pleasing. Physical participant information sheets were read, and consent forms were signed before participants began. The user clicked the image they chose, and the system presented the next pair until all comparisons were made. Each user was allocated a unique ID and image choice and image pair order presented to the user stored for analysis. Ten participants were recruited from University of Leeds PhD students, with an equal number of males and females, 80% were aged between 26-35 with the remaining 20% between 36-45, and 70% had master's degrees or equivalent (with the remainder having PhDs).

Modelling aesthetic value

The data from the paired-comparisons survey was modelled using the BT model using the 'BradleyTerry2' R package (Turner and Firth, 2012) with the value set relative to the baseline category (set a posteriori to be the highest-ranked image) (Zucco et al., 2019) and normalised between 0 and 1. The model predicts 'ability (α)' (also called the 'estimate' or 'worth' value), for clarity and ease of understanding in our study, the modelled value will henceforth be referred to as the 'aesthetic value'. The statistical significance of differences in value between each image and the baseline image (highest ranked image) is also included. Following Zucco et al. (2019), as it is not feasible for all *p*-values to be reported between all paired comparisons, bootstrapped confidence intervals for the aesthetic value and rank order of each image are reported. This involved drawing 1000 simulations for each image's position from a multivariate normal distribution with mean and variance-covariance matrix set to their empirical values, with each image's 5^{th} and 95^{th} percentile rank across all simulations reported.

Partial BT modelling

To investigate the potential of partial or incomplete paired comparisons (where participants only rate a subset of paired image comparisons) to model aesthetic value, the paired-comparisons data was modelled in parallel with differing numbers of responses (truncated at 104, 200, 300, 400, 500, 600 and 700 responses, in order of paired comparison, out of the total 780 comparisons) using the BT model. In this study we used a fully connected undirected 'graph' (the set of vertices (images) connected by edges (paired comparisons). This meant the lowest truncation was 104, as lower than this would have left the graph unconnected. This value is not theoretical and specific to our experiment and will vary with the same value for N due to randomization of the paired comparisons used in a partial dataset. Although methods exist to analyse partial matrices with unconnected graphs with variants of the BT model, we use the standard model which required a fully connected graph to allow the model to rank the images based on maximum likelihood estimates. To investigate the applicability to varying image datasets, three random subsets of 10 (25%), 20 (75%) and 30 (75%) images each were taken, and BT model analysis repeated, once again using truncated paired-comparison matrices for each. The total number of comparisons for each subset was 45 comparisons for 10 images, 190 comparisons for 20 images, 435 comparisons for the 30 images and 780 comparisons for the full set of 40 images. Kendall's tau-b was calculated to investigate correlation, due to its ability to handle tied ranks.

Regression analysis and mapping aesthetic values

Linear regression modelling was used, with the aesthetic value (from the full paired-comparison BT model) as the outcome variable. The 'waterway', 'watercourse', 'riparian zone' and 'body of water' predictors had the same presence distribution across 40 images, hence were grouped into a single collective variable. This resulted in 31 term synonym groups as predictor variables. Variance Inflation Factors (VIFs) were calculated to investigate multicollinearity, with the highest VIFs removed until all VIFs were under 10. Some collinearity is to be expected, due to the nature of the landscape type predictors and the use of synonym groups. Stepwise selection (both directions) was used, and non-significant predictors were successively removed until the model consisted of only significant predictors. Cross-validation was used to quantify uncertainty in the model. The final model was used to predict the aesthetic score for accessible areas within Yorkshire Dales, using for all 22,615 landscape-only Flickr images in the park and mapped at a 1 km^2 resolution, using the mean aesthetic estimate of all images within a cell. Mapping was undertaken in ESRI ArcMap (v.10.6), with a standard deviation (n=2.5) stretch applied to all visualised maps.

Results

Paired comparison survey

Our analysis revealed that perceived aesthetic value can be discerned through paired-comparisons and Bradley-Terry models, with LUCAS images having both a lower mean and rank for aesthetic value compared to Flickr images (Figure 3). Images were ranked by perceived aesthetic value , see Supplementary Information Appendix C. The estimates are provided relative to the baseline category (the highest-ranked image) set arbitrarily at zero, and then normalised between 0-1 for ease of interpretation. The statistical significances reported refer to the difference to each image and the baseline. The top two images are not significantly different from each other; hence there is some noise in the estimated values, though both are Flickr images. Remaining images are significantly distinguishable from each other ($P < 0.01$), compared to the baseline (highest scoring) image. Following Zucco et al. (2019), we computed bootstrapped confidence intervals for the rank order for each image in lieu of reporting p-values for all paired comparisons. The average standard error of the aesthetic value was 0.23, with the Flickr images having slightly less at 0.22 and LUCAS images having 0.23. The median estimate and rank were higher for Flickr images with 0.68 and 11.5 respectively, with LUCAS images having lower value of 0.41 and 30.5. Flickr images also dominated the higher the ranks, with 75% of the most aesthetic images being of Flickr origin, in agreement with our postulate that aesthetic preference is higher in non-random landscape images from social media.

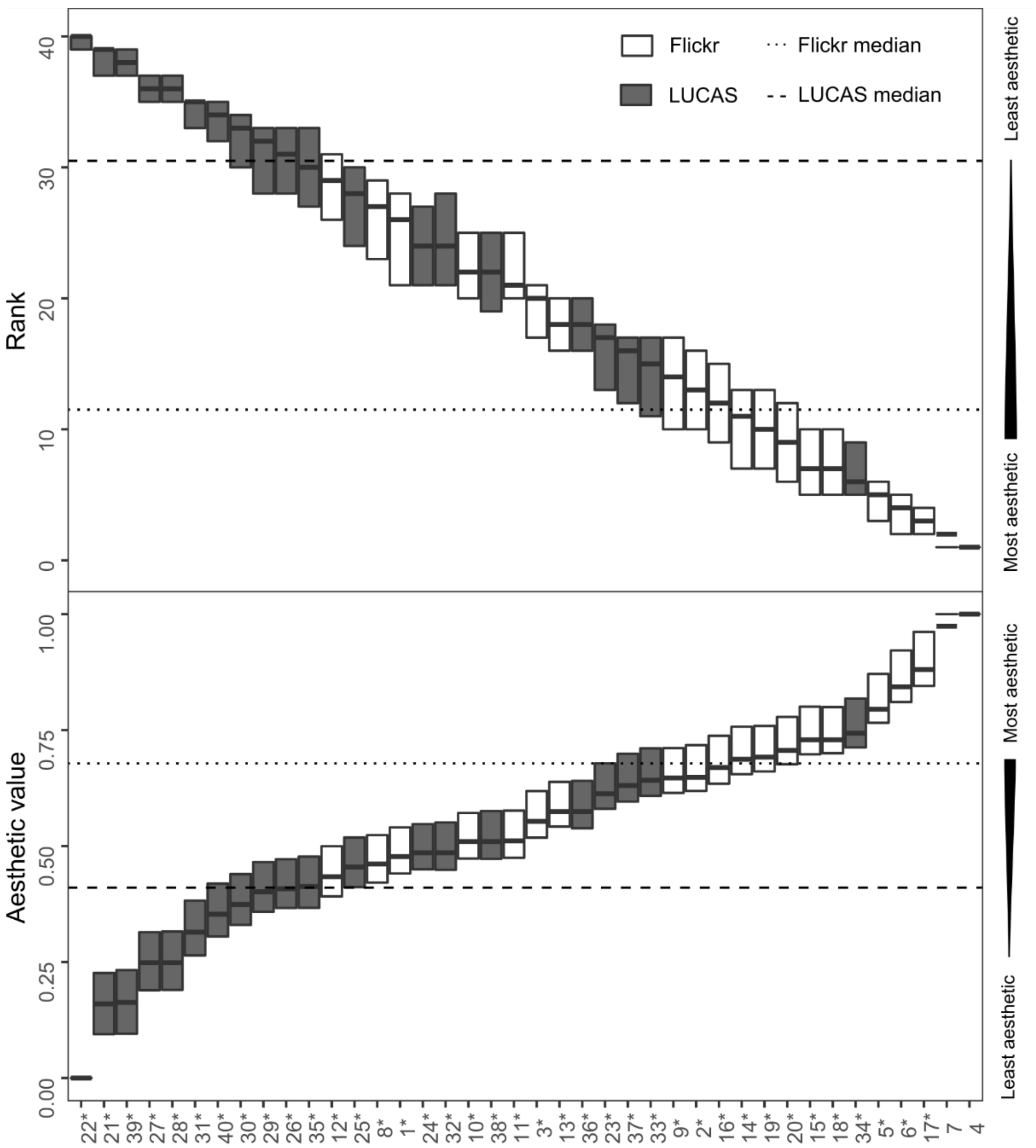

Figure 3. Estimated aesthetic value (Bradley-Terry model estimates) for forty samples images using complete paired comparisons from the Yorkshire Dales National Park. P-values compared to the baseline (highest value) image (04) (*P < 0.01). The CI's reports the 90% confidence intervals of aesthetic value and rank order of each image, computed using a 1000 simulation parametric bootstrap.

Partial paired comparison data

A set of seven partial (or incomplete) paired comparison subsets of the data at 16-90% of the total 780 comparisons, were modelled and compared to the full 100% model shown in Figure 4. Results show that even at 14% of the full set of pair-comparisons a strong correlation (R^2 of 0.93) between BT model estimates for full and partial set exists, increasing to 0.99 from 38%. The standard error increases with less responses, between 0.225 to 0.616 with the maximum width of the rank-order confidence interval increasing from 7 to 14 with the least responses BT-model (Supplementary Information Appendix C, Table C1). Differences are to be expected between varying response models, though correlation between all paired comparison models to the truncated paired comparisons models show a high level of similarities.

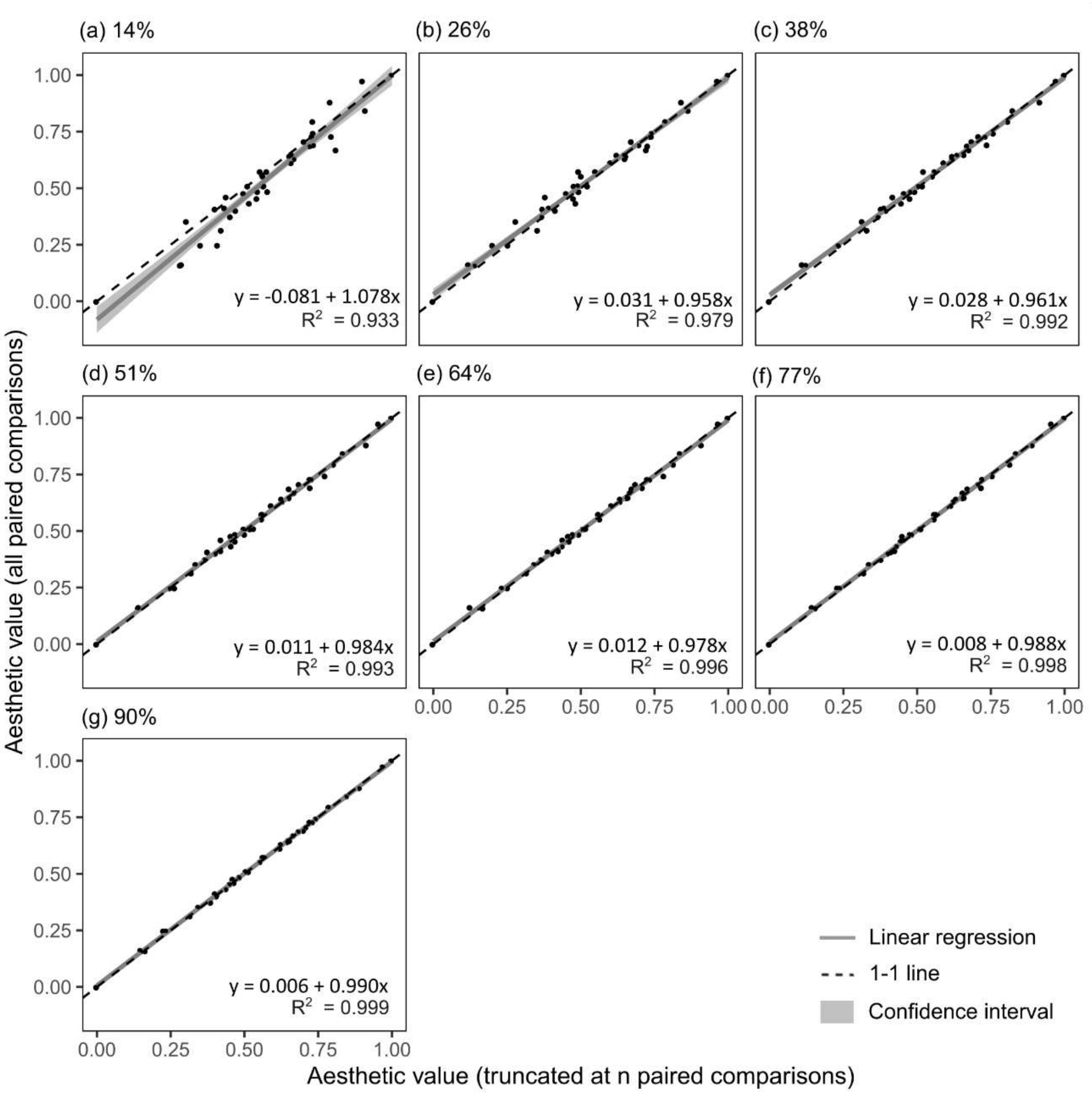

Figure 4. Complete paired comparison Bradley-Terry model estimates vs varying BT models using different number of paired comparisons (partial matrices) for forty sample images. Adjusted R^2 shown.

To demonstrate the transferability of the method, random subsets of 10 (25%), 20 (75%) and 30 (75%) images were modelled using the Bradley-Terry model (each subset modelled in parallel with differing levels of partial paired-comparison data). Kendall's Tau-b was used to indicate the correlation between the partial and full paired comparison data within each subset independently) (Figure 5). It can be seen that Kendall's tau-b reaches higher values at lower paired comparison truncations the higher the sample size, though a tau of over 0.80 can be achieved having at least 20% paired comparisons in any of the subsets.

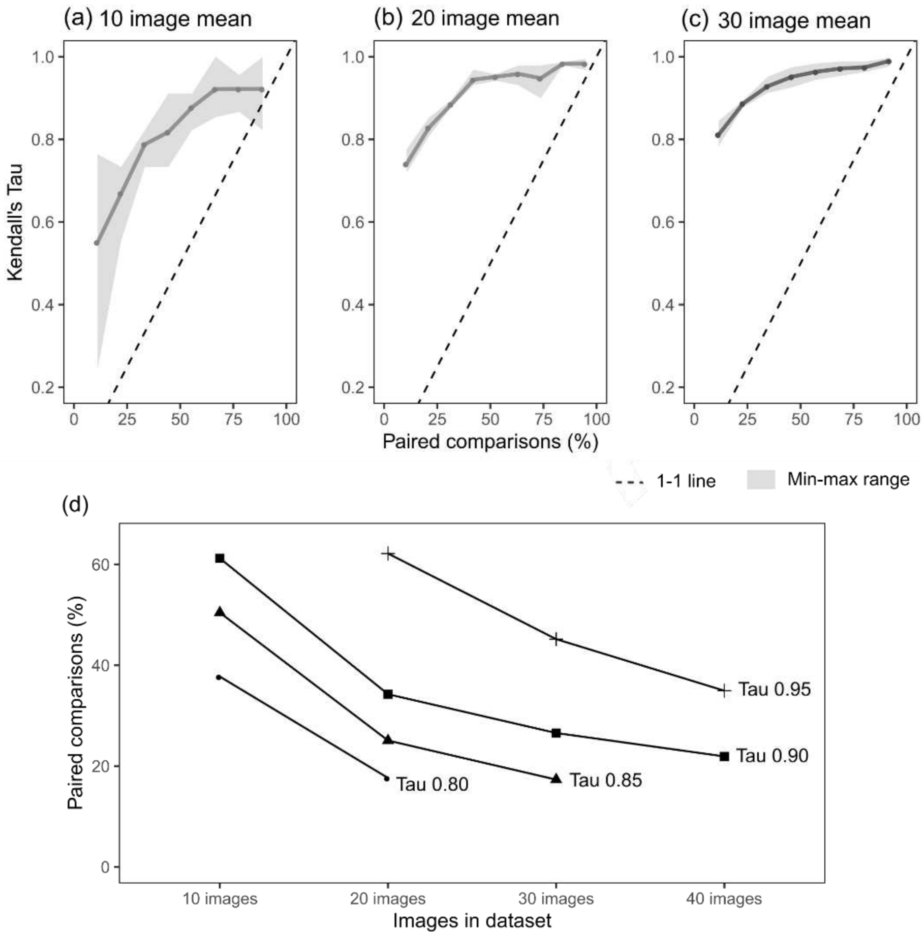

Figure 5. Plot showing the correlation between complete paired comparison BT model estimates and varying BT models using different number of paired comparisons (partial matrices) for three subsets of the dataset: 10, 20 and 30 images, with three replicates (n=3). Panel (d) shows multiple Kendall's Tau-b values for partial paired-comparisons (in % of total number of possible pairs) by images used. Tau-b values used in (d) are intercept values from a linear model for respective (a), (b) and (c) BT models.

Predictive modelling

The BT estimates for the original complete BT model (Figure 3) were regressed onto synonym groups derived from content in landscape images from the Yorkshire Dales National Park. The final model has an adjusted R^2 of 0.62 and an RMSE of 0.17 (based on 8-fold cross-validation) with 8 negative predictors and 11 positive predictors (Table 1 and Figure 6), with the latter having an overall higher level of significance. The most important of the positive predictors were 'rural areas' and 'mountain' with estimates of 0.671 and 0.60, with 'vegetation', 'ecoregion', 'plain', 'stream', 'prairie' and 'fell' all having estimates between 0.29 and 0.44. The strongest negative predictor was 'field' with a value of -0.75, followed by 'land lot', 'steppe', and 'highland', with estimates ranging from -0.33 to -0.46. Whereas the model explains a significant percentage of the variance using regression based on machine learning (using reduced term synonym groups), the results suggest that there are factors outside of the synonym groups that impact aesthetic preference, as would be expected.

Table 1. Linear regression model (using forty sample images) after stepwise and Variance Inflation Factor selection (VIF<10) and removal of non-significant variables. This resulted in R^2 of 0.797 (adjusted R^2 = 0.622) with model p-value <0.001. Variables p-values are indicated as *** <0.001, ** <0.01, * <0.05.

	Aesthetic value ability	
Predictors	*Estimates*	*CI*
(Intercept)	0.05	-0.17 – 0.27
Rural area	0.71 ***	0.43 – 0.99
Mountain	0.60 ***	0.35 – 0.84
Vegetation	0.44 ***	0.29 – 0.60
Ecoregion	0.35 **	0.17 – 0.52
Plain	0.33 **	0.11 – 0.55
Stream	0.32 ***	0.17 – 0.46
Prairie	0.30 **	0.10 – 0.50
Fell	0.29 **	0.10 – 0.48
Mountainous landforms	0.20 *	0.05 – 0.35
Green	0.16 **	0.05 – 0.27
Farm	-0.12 *	-0.24 – -0.01
Tundra	-0.19 *	-0.36 – -0.01
Hill	-0.24 *	-0.41 – -0.07
Water	-0.24 *	-0.42 – -0.06
Highland	-0.33 **	-0.53 – -0.14
Steppe	-0.34 **	-0.54 – -0.14
Land lot	-0.46 **	-0.70 – -0.23
Field	-0.75 ***	-1.04 – -0.45

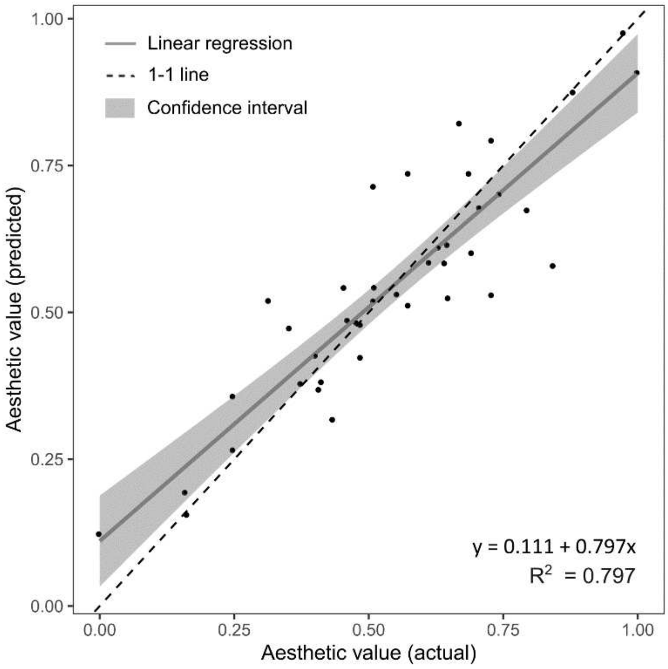

Figure 6. Predicted aesthetic estimates vs actual BT model estimates using the original full model with all images and paired comparisons. Note: all values normalised between 0 and 1.

Mapping aesthetic value

The regression model was used to predict aesthetic value for all landscape for the entirety of the Yorkshire Dales National Park (Figure 7). High values can be seen across the National Park. Highlights include the region north of Sedbergh, a hilly area with some including the Howgill Fells which is used by climbers and known locally for its picturesque views. White spaces in the map are 34% (752 km^2) of all pixels, where no Flickr landscape photos were found and are noticeably away from easy access (roads). An area with many roads and the River Swale, to the north of Hawes and Aysgarth, also exhibits high aesthetic value. Malham Moor, north-east of Settle, has high valued pixels, as does the village Ingleton, and Bolton Priory (Augustinian priory ruins set in riparian rural landscape). To explore the visual correlation between the areas with high aesthetic value and number of photos taken, the top 20% and photo density were mapped (Figure 8) and showed visual similarity in spatial pattern.

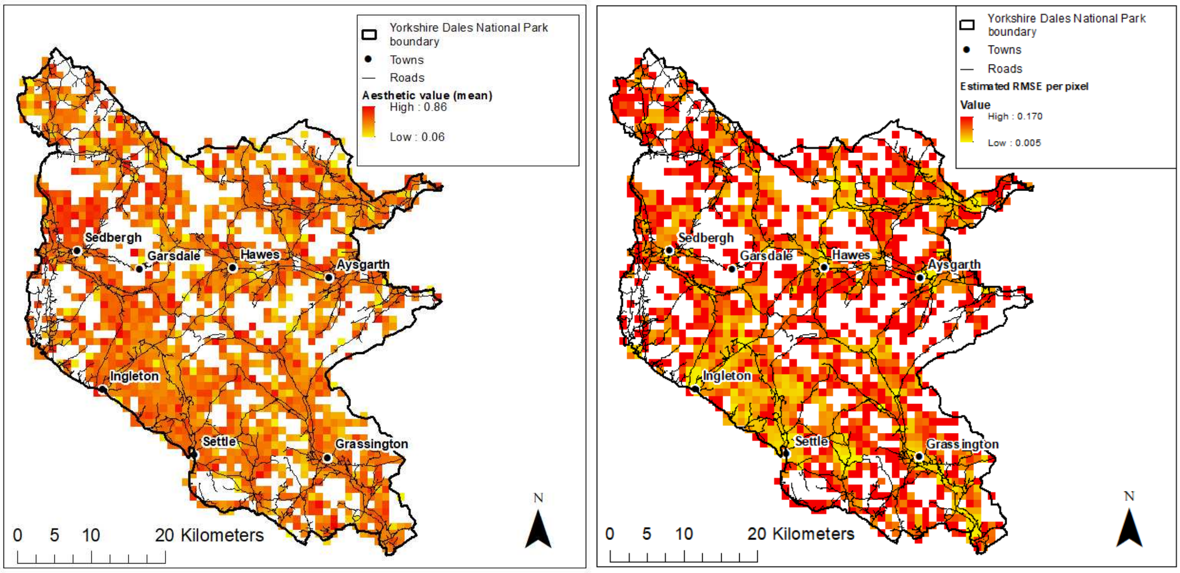

Figure 7. (a) Predicted aesthetic values for the Yorkshire Dales National Park using 22,615 images (prefiltered to only landscape images), (b) estimated RMSE per pixel. White space between pixels indicate areas where no landscape images were present. © Crown Copyright and database right 2019. **[COLOUR PRINT]**

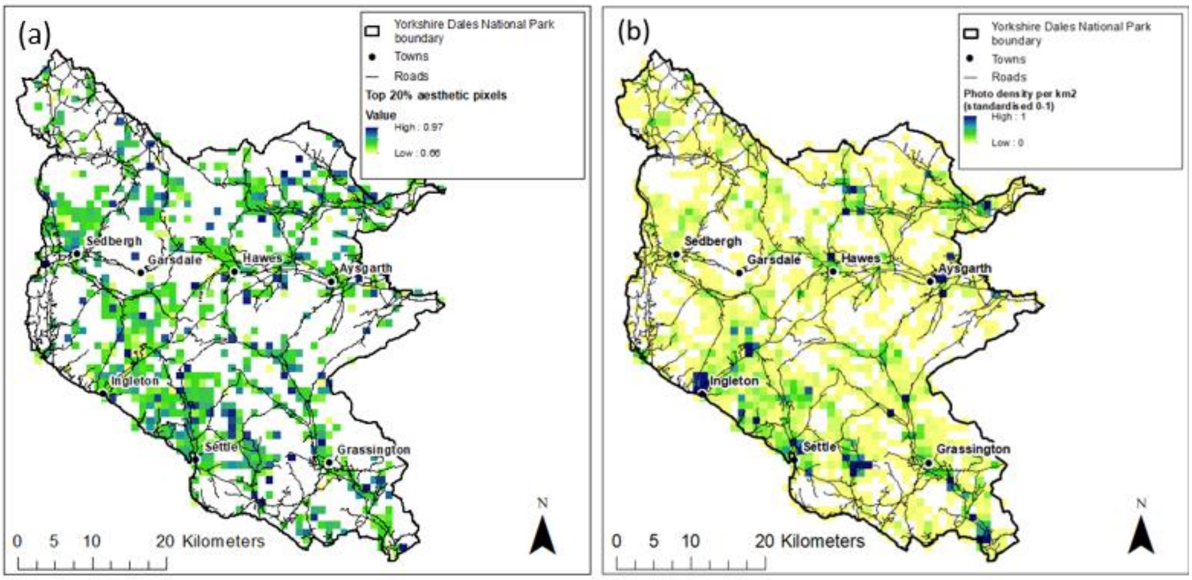

Figure 8. (a) Top 20% of predicted aesthetic values, (b) density of photos taken, per km^2 in the Yorkshire Dales National Park. White space between pixels indicate areas where no landscape images were present. © Crown Copyright and database right 2019.

Lastly, images with high and low aesthetic value from the National Park were extracted and visually inspected (Figure 9). High scoring images can be seen to be exhibit more ‘complexity’, having a ‘hilly’ character, with the horizon not being complexly ‘horizontal’. There also appears to be a variety of components in each image, including vegetation (both low, i.e. grass, and high such as trees) and water. There are also images of snow, though the underlying landscape can be seen at least in part. The low scoring images often show a flatter horizon, with large swathes of low green vegetation, i.e. fields and grassland. Visual analysis shows that the techniques culminating in the final mapping of aesthetic value suggest the method was robust.

Figure 9. The top five (a1 – a5) and bottom five (b1 – b5) images with predicted standardised (0-1) aesthetic value estimates from 2,428 available Creative Commons images within the dataset (from a total of 22,615 images that were identified as landscape images). Note, estimates are rounded to two decimal places. Where multiple images had the same aesthetic value estimates, the images were selected based on numerical descending ID number of the image. Grey upper and lower bounding bars and black outlines were added to images for this figure for clarity and are not present in the originals. Full Creative Commons attributions are given in Supplementary Information Appendix E. **[COLOUR PRINT]**

Discussion

The use of paired-comparisons, while remediating the 'endpoints' of inter-personal variability of Likert scale surveys, is difficult to upscale to larger number of photos. This study showed that a partial matrix of paired-comparison data can be used to provide results that are not dissimilar from using complete paired-comparison data to extract aesthetic preference from social media images. This highlights the potential of the techniques demonstrated to combat the N^2 challenge from using paired comparison methods whilst still maintaining the ability to get reliable R^2 values. We found very good agreement with only 20% of the paired comparisons. Additionally, similar patterns in the data can also been seen in different values of N. Results were expected, as other studies such as Zucco et al. (2019) have successfully used partial paired comparison datasets, having used 275 out of 666 potential comparison sets (or 41%).

Our final model using regression based on machine learning and content tags reduced by synonym grouping explained a large amount of the variance in the BT model output. When used at the landscape scale, the final maps showed areas with high aesthetic value were often those where many photos were taken (Figure 8). This affirms the expectation that landscapes with high aesthetic value attract more recreational users, and thus have more photos taken (and uploaded to Flickr) (as this would translate into a high photograph user-days (PUD) value (e.g. Gosal et al., (2019)). The resulting high-value aesthetic images from the upscaled data showed a preference for landscape complexity, which has been shown to be a driver for preference (Ode et al., 2010). The models also showed a positive impact of mountains, mountainous landforms and streams. This partially follows van Zanten et al. (2016) who found that the strongest predictors for high aesthetic value were hills and mountains, while 'hills' in our study show a moderate negative effect, perhaps a result of the differentiation in the Google Vision tags for these terms. Though our results are confirmed by Peña et al. (2015) whom found that personal aesthetic assessments were predominantly based on naturalness of an area and how land use management impacted it. They found that diverse, mountainous and those landscapes with water bodies were preferred over flat, homogenous, water-less landscapes. Casado-Arzuaga et al. (2014) found that high aesthetic value areas were corresponded with more natural landscapes, especially coastal ecosystems, rough summits, forest/pasture mosaic areas and rural settlements. They found that the human influence of farming, in terms of farmhouse, livestock or crops) added aesthetic value in landscape compared to those landscape that no longer had farming associations. This helps to explain our own result of rural area being the strongest positive predictor in our model.

Areas of high landscape coherence are often considered of higher aesthetic value, including those physiognomic classes with agricultural areas, forests, water bodies and areas of transitional vegetation, with low coherence seen in areas with urban fabric and bare rocks (Karasov et al., 2020). This high coherence can be seen in our results (i.e. positive predictors including rural area, streams, ecoregion, prairie and 'green'. Field, land lot, steppe and tundra, all negative predictors in our study are indicative of low coherence areas.

It has also been found that high landscape aesthetic quality in mountain ranges in Germany, riverine areas, coastal areas and lower in urban areas (Hermes et al., 2018). Our results showing mountainous landscape, and mountains having positive effects reinforce Hermes' et al. (2018) study. It has been found that viewpoints, agricultural land and cultural/historical features contributed highly landscape aesthetic capacity (Langemeyer et al., 2018). Interestingly, Langemeyer et al. (2018) found that context impacted landscape aesthetic capacity. For example, in littoral-mountainous landscapes, it was the presence of sea and forest elements that increased value, in mountainous landscapes the crest line (scenic-ness in the background) and in urban landscapes, it was rivers and hills.

It has been suggested that the attractiveness of landscapes are linked to its physical attributes (Casado-Arzuaga et al., 2014; De Vries et al., 2007), and our results would confirm that features of landscapes identified from photographs are indeed strong predictors of aesthetic value, and generally is consistent with other studies that have investigated the impact of landscape characteristics on landscape aesthetics. Our study is coherent with Tieskens et al. (2018), whom also found that grass and water were positively predictive of high aesthetic value the close the relative feature was to the geolocated photo. Though in contact, forest was also predictive, though is not one of our significant predictors in our model.

Seresinhe et al. (2017b) used a neural network approach to extract features from images and used scenic scores from an online platform. They found that mountain-related terms such as 'mountain snowy', 'mountain, 'mountain' paths were positive predictors of scenic-ness, consistent with our results. The term 'green' was also weakly positive, and the term 'farm' weakly negative, for both our studies. Though on some terms, such as tundra. Hence it is suggested that use of automated processes can create more consistency and aid in the removal of human error for feature extraction.

Whereas the regression model explained a large proposition of the variance, other factors in the photographs must have contributed to aesthetic preference. Non-symmetrical landscape images are preferred over symmetrical images, which was not analysed in our study (Bertamini et al., 2019). This may explain why more unsymmetrical images ranked higher in the examples given in Figure 9. Seasonal stages have also been found to influence preference of landscape elements, with flowering stages most liked (Junge et al., 2015), and indeed the use of photographs from all seasons in this study was a limitation. Coloured flowers, especially blue ones, have been found to be preferred (Hůla and Flegr, 2016). Colours generally in the images may have impacted aesthetic preference. For example, Huang and Lin (2019) have found that in mountainous landscapes, magenta-green colour diversity is preferred.

By using only ten people in this study, similar in age and education level, with an interest in geography as a subject, there was a potential limitation in not being representation of the general population. Though all participants lived and work within 30km of the study area, hence were assumed to have some familiarity of the area. While some studies have shown that landscape preference can be impacted by socio-demographic factors (i.e. age, gender and residential experience (Luo et al., 2019; Lyons, 1983)), Kalivoda et al. (2014) argues that positively rated landscapes share broad consensus across socio-demographic characteristics. Indeed, while the results in Figure 7 may be culturally context-dependent (because of our respondents' sample) the similarity to PUDs (Figure 8) supports the argument in the latter study.

The upscaling and transferability of the method is dependent on the availability of photos for a given landscape. LUCAS photos are available across the EU states, with social media data, including Flickr, being available for 61% (of 5401) national parks globally (Tenkanen et al., 2017). The method employed is restricted in that it only generates aesthetic values for those areas that are accessible, or at least 'visually' accessible. Future work should address larger and more diverse photos and respondents sample size, other photos' qualities such as symmetry and seasonality.

Being able to map aesthetic preferences for any given protected are important for management decision making. van Zanten et al. (2016b) found that within agricultural landscapes hedgerows and tree lines where valued for aesthetics and recreation value in the Netherlands, in Germany, it was trees and crop diversity. Hence the values of aesthetic services can vary geographically, and hence approaches such as ours that are highly context-relevant are important for advising management decisions. Section 61 of the Environment Act 1995 assert that English National Parks should 'promote opportunities for the understanding and enjoyment of the special qualities [of the national parks] by the public' (Yorkshire Dales National Park Authority, 2018a). With UK's exit to the Common Agricultural Policy, a new land management system for farming system will have unknown consequences for the parks landscape (Yorkshire Dales National Park Authority, 2018a). Hence it becomes even more important to assess the current aesthetic assets that are held. This study demonstrates an up-scalable approach that only uses free and publicly available photos and using opens-sourced tools (mostly in R) for analysis.

Conclusion

Landscape aesthetics are nuanced. Our methods help to elucidate the subtle nature of landscape aesthetics through combining techniques that have been used in other fields such as BT models and machine learning. Aesthetics are both spatially and temporally explicit and subject to a myriad of factors, but the use of public data and advanced algorithms opens a potential to successfully value landscape aesthetics at large extents – which is key to prevent further degradation of our natural heritage.

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