"Does wilderness correlate with scenicness?" – A quantitative case study in Wales

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Summary

The term "scenicness" refers to the perceived aesthetic and scenic beauty of observed landscapes. Crowdsourced measures of scenicness from the *Scenic-Or-Not* website provide an opportunity to explore public perceptions of landscape beauty and how they relate to other landscape metrics. This paper compares crowdsourced measures of scenicness with a number of formal landscape measures that are commonly used to construct landscape wildness and wilderness metrics using both global and local regressions. The results indicate a positive relationships between crowdsourced scenic ratings and formal wilderness measures but also suggest that features more commonly associated with built environments should be included in scenicness assessment.

KEYWORDS: Scenicness, Wilderness, *Scenic-Or-Not*, Geographically Weighted Regression.

1. Introduction

Scenicness refers to aesthetic pleasure of observers via visual perception of naturally and artificially scenic beauty. Due to variations in human perception and aesthetic judgement of the environment caused by different cultural backgrounds (Zube and Pitt, 1981), age, gender, social stratum (Dramstad et al., 2006, Hunziker et al., 2008, Tveit, 2009), it can be difficult to determine objective measures to quantify how scenic people perceive an area to be. Thus far, scenicness assessments have featured a perception and expert-based methods (Daniel, 2001). The former approach has dominated applied environmental perception and landscape assessment research through on-site perceptual surveys of observers usually on a small scale, leading to highly localised results with little generalizability and relatively expensive and time consuming methods (Beza, 2010). The latter approaches quantitatively examine well defined visual properties and biophysical features of the landscape resulting in high efficiency but low local relevance and reliability. Among expert-based methods, GIS-modeling comprising statistics, such as population density, land use, has ubiquitously been applied in large-scale environmental management practice (Seresinhe et al., 2017a). To consolidate both on-site surveys and expert-based approaches, hybrid methods have been proposed to better reflect public perceptions of scenicness and thereby to better support environmental management and more effective representation of visual aesthetic quality in management decisions and policies (Daniel, 2001).

The *Scenic-Or-Not* website (http://scenic.mysociety.org/) which is an online game set up to collect and share crowdsourced data across Great Britain. It seeks to provide measures to support quantitative analyses of the scenicness impacts on human wellbeing (Seresinhe et al., 2015). Participants are invited to rate random geotagged photos on an integer scale according to scenic beauty (from 1 = least beautiful

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to 10 = most beautiful). Each photo is located within a 1 km grid square of Great Britain and sourced from *Geograph* (http://www.geograph.org.uk/), an open online project collecting geotagged photographs for each square kilometre of Great Britain and Ireland. The scenicness data has resulted in a new avenue of research (Seresinhe et al., 2017a).

Shared, crowdsourced photographs offer opportunities for gathering large-scale data on human perceptions of the environment. These can be used to examine correlations between image properties (e.g. colour composition) and semantic attributes (e.g. scene categories) (Workman et al., 2017). Previous studies analysing the ratings and photos from *Scenic-Or-Not* have investigated the links between scenicness and land cover (Stadler et al., 2011), and scenicness and health (Seresinhe et al., 2015). Other recent research in computer vision has shown that not only natural features but also man-made features can be considered as scenic (Seresinhe et al., 2017b). Models that have linked *Flickr* and *OpenStreetMap* data have been found to improve scenicness estimates and prediction (Seresinhe et al., 2017a). However, 5% of the grid squares from *Scenic-Or-Not* database are still lacking, as with many crowdsourced data, there can be issues with data-sparsity which has been addressed by incorporating both ground-level and overhead imagery evaluate the scenicness of a region (Workman et al., 2017).

Wilderness definitions focus on the natural state of the environment with no human settlement and low related impacts (Carver et al., 2002) and as yet it is unclear how wilderness measures could contribute to scenicness assessments. For these reasons this study sought to evaluate to what extent the beauty of scenes coincides with the wilderness attributes.

2. Methodology

Data and Case Study

A subset of *Scenic-Or-Not* data within Wales was used as the study area (Figure 1). There are 19,258 images in this subset, each of which had been rated at least 3 times until February, 2015. The mean score of scenicness for each representative image was adopted in this study. For each location of the photo, four of wilderness indicators (Fritz and Carver, 1998) were extracted as independent variables. These include:

(1) Biophysical Naturalness: the degree to which the natural environment is free of biophysical disturbances due to human occupation or exploitation.
(2) Apparent Naturalness: the degree to which the landscape is free from the presence of the permanent structures of modern society.
(3) Remoteness from Access: remoteness from established mechanised access routes.
(4) Remoteness from Settlement: remoteness from points of permanent human occupation.

A global regression model was specified as follows:

$$y_i = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij} + \varepsilon_i \tag{1}$$

where for observations indexed by $i = 1, \ldots, n$, y_i is the response variable, x_{ij} is the value of the j^{th} predictor variable, m is the number of predictor variables, β_0 is the intercept term, β_j is the regression coefficient for the j^{th} predictor variable and ϵ_i is the random error term.

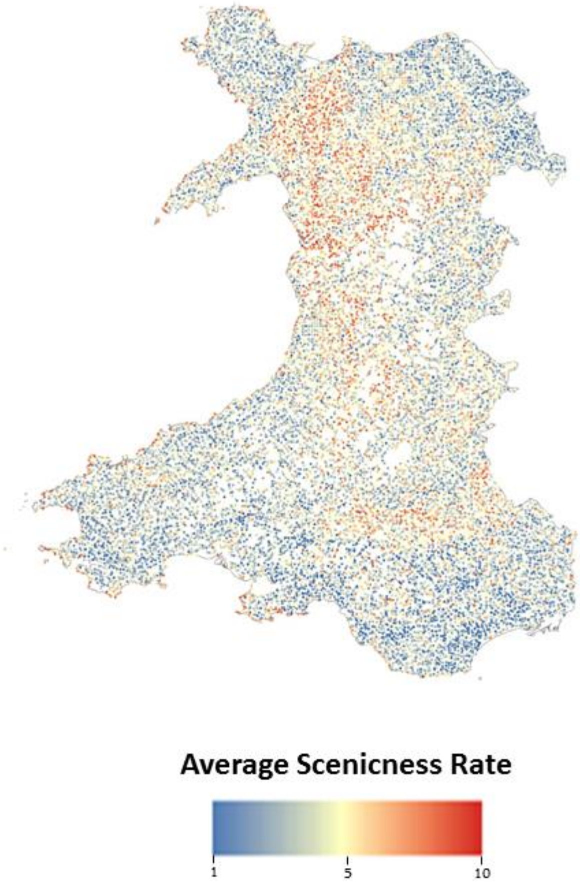

Figure 1 Average ratings of *Scenic-Or-Not* dataset in Wales

Next a GWR was undertaken. This is similar in form to linear regression, except that GWR calculates a series of local linear regressions rather than one global one. A GWR model has locations associated with the coefficient terms:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{m} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \tag{2}$$

where (u_i, v_i) is the spatial location of the i^{th} observation and $\beta_j(u_i, v_i)$ is a realization of the continuous function $\beta_j(u, v)$ at point i. The geographical weighting results in data nearer to the kernel centre making a greater contribution to the estimation of local regression coefficients at each local regression calibration point k. For this study, the weights were generated using a *bisquare* kernel, which for the bandwidth parameter r_k is defined by:

$$w_{ik} = \left(1 - (d_{ik}/r_k)^2\right)^2 \text{ if } d_{ik} \le r_k \qquad w_{ik} = 0 \qquad \text{otherwise} \tag{3}$$

Where the bandwidth can be specified as a fixed (constant) distance value, or in an adaptive, varying distance way, where the number of nearest neighbours is fixed (constant). In this case, fixed bandwidths were chosen as the data are on a regular grid.

3. Results

OLS regression

The result of the global regression (**Table 1**) suggest that all the wilderness variables are positively correlated with average scenic ratings with an AICc coefficient of 65186.57. The variable of biophysical naturalness is the most significant parameter estimate associated with 1.337 increase of scenicness shown. The output also reveals that the parameter of remoteness from settlement is statistically less significant as its p-value (0.0208) is much greater than the other variables.

Table 1 Ordinary Least Squares (OLS) results.

Variable	Estimate	Std. Error	t-value	p-value
Intercept	2.399e+00	3.551e-02	67.576	<2e-16
Biophysical naturalness	1.337e+00	5.285e-02	25.305	<2e-16
Apparent naturalness	5.692e-01	1.478e-02	38.504	<2e-16
Remoteness from access	7.486e-02	3.364e-03	22.255	<2e-16
Remoteness from settlement	3.254e-05	1.408e-05	2.311	0.0208
R-squared	0.2626			
Adjusted R-squared	0.2625			
AICc	65186.57			

GWR regression

In the next step, a local GW model was applied to explore the presence of spatial variability between wilderness variables and scenic beauty. For this, an optimal bandwidth of 14.2645 km was estimated by minimising the cross validation (CV) score for a fixed bisquare kernel to control how much data was included in each local model and the degree of smoothing in the GW model. The improvement of model fit from the local model was evidenced by a lower corrected Akaike Information Criterion (AICc) of 63825.3, indicating a non-stationary relationship.

Both of the naturalness factors exhibit larger variability of the estimate parameters than remoteness factors demonstrated by the higher interquartile range (IQR), summarised in **Table 2**. In particular, the parameter of remoteness from settlement portrayed the limited spatial variability with the lowest IQR of 0.000309. Yet, there were spatial variabilities of all the wilderness variables that affected human perception of scenic beauty, which can be evaluated through a visual representation of the parameter estimate surfaces shown as **Figure 2**.

Table 2 Geographical weighted regression (GWR) results.

Variable	1st Quartile	Median	3rd Quartile	IQR
Intercept	2.207e+00	2.892e+00	3.393e+00	5.1370
Biophysical naturalness	7.970e-01	1.283e+00	1.743e+00	9.46e-01
Apparent naturalness	2.839e-01	4.369e-01	5.754e-01	2.92e-01
Remoteness from access	3.870e-02	7.469e-02	1.098e-01	7.11e-02
Remoteness from settlement	-5.584e-05	7.291e-05	2.531e-04	3.09e-04
R-squared	0.3509311			
Adjusted R-squared	0.325575			
AICc	63825.3			

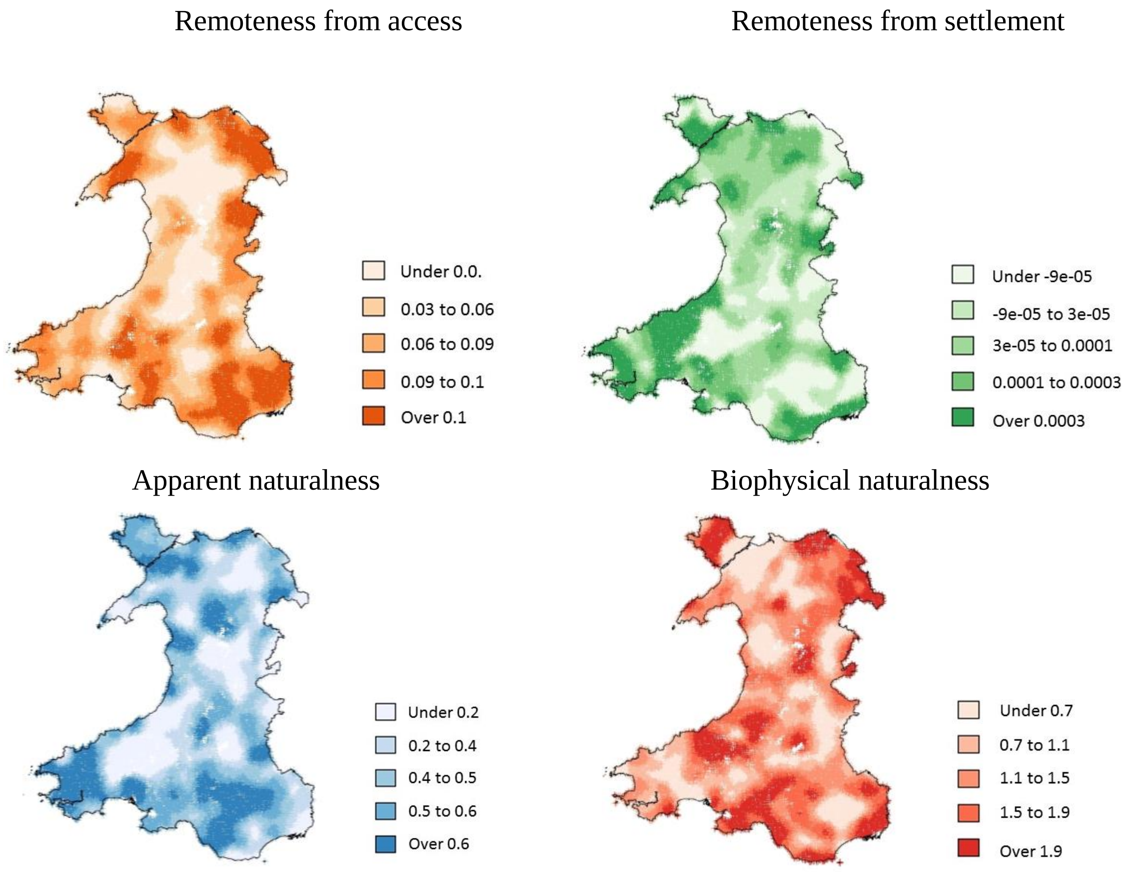

Figure 2 GWR Coefficient estimates of the four wilderness variables

4. Discussion

The result of the global model revealed that the naturalness factors of wildernesss measures contribute more than the remoteness factors to human aesthetic perception of the landscapes. The descriptive statistics also proved the variable of remoteness from settlement to be statistically insignificant, indicating that measures of scenicness in some places should include built environment features, such as “Viaduct” and “Aqueduct” (Seresinhe et al., 2017b). Additionally, the presence of significant spatial variabilities in the relations between scenicness and landscape naturalness were identified by the local model. To be noted, that the biophysical aspect of the naturalness quality is surprisingly more significant than the apparent naturalness.

A few issues suggest areas for future research. In the regression model, the use of the average ratings as the dependent variable was more likely to be skewed by unusual opinions about scenic beauty and also flattened the distribution of user ratings. Second, the varied number of user ratings for each photo can be considered to standardise the observer’s ratings. Last, the variation in vantage point and orientation in the square also has impact on measures of scenic beauty. The actual physical locations of scene pictures usually differ from the published location leading to different wilderness character. Thus, detailed information such as EXIF is needed to be taken into account to derive an accurate prediction model.

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6. Biography

Professor **Lex Comber** holds a Chair in Spatial Data Analytics at the School of Geography. Lex is a leading international researcher in many areas of spatial science and geocomputation, with publications in accessibility, facility location optimisation, graph and network theory, spatial data uncertainty, citizen science, land use / land cover and remote sensing.

Dr **Steve Carver** is a senior lecturer at the School of Geography and is Director of the Wildland Research Institute. He has worked extensively on the development of wild land mapping and evaluation methodologies and has tested and applied these across a variety of locations and spatial scales including Scotland, England, Britain, Europe, and North America.

Yi-Min Chang Chien is currently a second year Ph.D. student at the School of Geography interested in spatio-temproal analysis, spatial big data and geospatial intelligence.

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