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Full Research Article

Assessing preferences for rural landscapes: An attribute based choice modelling approach

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Abstract. This study adopts a choice modelling framework to disentangle individual preferences for rural landscape attributes based on the viewing of photographs of the Irish countryside. Using ordered logit and standard panel and pooled regression models, societal preferences are quantified for rural landscape attributes, grouped into natural, agricultural and human-built non-agricultural categories. The preferences of 430 individuals towards 50 rural landscape photographs are analysed. The results show positive preferences for landscapes with natural attributes such as cliffs, mountainous features, water and native trees, as well as preferences for neat/managed agricultural landscapes and traditional human-built features such as stone walls and planted hedgerows. The study shows negative preferences for features such as flooding, unmanaged landscapes, industrial turf cutting and mechanised features such as wind turbines. There is significant preference heterogeneity observed across the sample particularity across the urban-rural residency divide. It is argued that analysing preferences for specific attributes of landscapes rather than preferences for individual landscape photographs allows for further applications particularly in the area of simulation.

Keywords. Rural landscapes, choice modelling, ordered logit, attribute preference heterogeneity.

JEL codes. Q18, Q24, Q57.

1. Introduction

Agriculture is a multifunctional, natural resource based sector that takes place predominately in rural areas. It provides private goods like the '5 fs': food, feed, fuel, fibre and forest (Kern, 2002), generating income for farm families and contributing to the aesthetic character of human-ecological systems. These landscapes also support the delivery of other public goods such as recreation and cultural heritage (Kantelhardt *et al.*, 2015)

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and ecosystem services (ES) relating to greenhouse gas emissions, water quality and biodiversity (Vanni, 2014; van Zanten *et al.*, 2014; OECD, 2015; Kantelhardt, 2006). These benefits, supplied by a sustainable agricultural sector, are reflected at EU policy level with increasing levels of funding dedicated to protecting rural landscapes and providing additional public goods from farming.

As landscape values are often perceived as public goods, in the sense that they are non-excludable and non-rival in consumption, markets cannot place a price on landscape features and quality of landscape services (Hanley *et al.*, 2009), nor can they guarantee their adequate provision (Schaller *et al.*, 2018; Villanueva *et al.*, 2015; Rodríguez-Entrena *et al.*, 2017). Thus, where there is a market failure, there is a case that governments should implement measures to ensure an adequate provision. To do that however knowledge is required in terms of the preferences of society for alternative landscape types and features.

A wide range of studies, using different methodologies, have attempted to examine rural landscape preferences and values in order to guide policy and better target expenditure to the most 'valued' landscapes. There are a number of studies that use expert judgement to assess the aesthetic quality of landscapes (Frank *et al.*, 2013; Hermes *et al.*, 2018). However, the perception of value may vary with perspective. For example, land owners and agricultural scientists may place a higher value on landscape attributes that involve the delivery of provisioning of ecosystem services, while members of the general public may subjectively place a higher value on cultural ecosystem services such as the aesthetics and recreational opportunities (Lothian, 1999). Thus expert opinion may not reflect what is of value personally to individuals or the wider population (Tveit, 2009).

Elsewhere, Kirillova *et al.* (2014) and Plieninger *et al.* (2013) perform a qualitative assessment of the cultural importance of landscapes, while willingness to pay (WTP) is assessed by Hynes *et al.* (2011; van Berkel and Verburg, (2014); Rodríguez-Entrena *et al.*, (2017); Dupras *et al.*, (2018); Bernués *et al.*, (2019) and Huber and Finger, (2019). The publics' stated preferences for landscapes and their features have also been surveyed (Howley, 2011; Howley *et al.*, 2012; Schirpke *et al.*, 2016, Santos-Martín *et al.*, 2019). Stated preference surveys often measure landscapes in a holistic way focusing on concepts or characteristics reflected in the landscape (Ives and Kendal, 2013; Tveit *et al.*, 2006).

Many landscape preference studies also employ non-monetary techniques where landscapes are assessed through rankings of a number of photographs, or monetary techniques to estimate direct and indirect use values (e.g. forest fibres) and/or non-use values (e.g. biodiversity, wilderness, spiritual) for preserving landscapes (García-Llorente *et al.*, 2012). Assessments based on cognitive attributes, such as landscape coherence, mystery, safety, and naturalness, provide a holistic assessment of a visual entity through its single components, rather than defining or focusing on specific physical landscape attributes, such as tree density or presence of hedges (Tagliafierro *et al.*, 2013; van Zanten *et al.*, 2014). Hynes and Campbell (2011) analysed the most appropriate economic valuation methodologies for agri-environment policies. They concluded that a holistic valuation approach should be used where the objective is the valuation of the landscape as a whole, whereas an attribute-based approach is appropriate if the objective is to understand preferences for individual components, which may allow for extrapolation using other GIS datasets in policy evaluation.

Choice experiments have been utilised to assess the preference for individual characteristics (Hynes and Campbell, 2011; Rodríguez-Entrena *et al.*, 2017; Dupras *et al.*, 2018). Although they present monetary measures of the willingness to pay for landscape attributes, there is a limit to how many attributes can be considered, albeit some papers (such as Bernués *et al.*, 2019) have an extensive array of choice attributes. Thus, it may be difficult to apply a choice experiment methodology to assess the preferences for a wide variety of landscape characteristics. García-Llorente *et al.* (2012) used photographs within the contingent valuation method to examine preferences for alternative landscape types. Follow-up expert opinion was employed to relate the observed willingness to pay for ecosystem services connected to the different landscapes in the photographs.

Two studies of particular relevance to this research are Howley (2011) and Schirpke *et al.* (2016). Howley (2011) assessed the effect of personal, geographic and environmental value orientations on landscape preferences. They did not however examine how the landscape attributes themselves could influence preferences or whether the potential effects could vary across survey respondents according to their personal, socio-demographic and geographic characteristics. Schirpke *et al.* (2016) similarly examined attitudes in relation to landscape images by assembling specific landscape attributes using viewsheds from a digital elevation model. Although Schirpke *et al.* (2016) consider the relationship between socio-economic characteristics and holistic image-based landscape attributes (as does Howley, 2011), their study does not consider the differential preference for specific landscape preferences across socio-demographic characteristics.

This paper aims to contribute to the literature of landscape preference valuation by (a) investigating whether individuals' characteristics interact with landscape attributes, and (b) how these interactions may ultimately affect public preferences for landscapes. The paper used data from Howley's (2011) analysis and builds on Schirpke *et al.* (2016)'s approach by applying expert judgement as opposed to a combination of GIS-based and observational attributes to each of the photos. The literature is extended by utilising an attribute choice framework to disentangle individual preferences for a holistic image of a landscape photograph into preferences for specific attributes of that landscape. The approach adopted in this paper facilitates the creation of a formalised model of landscape preferences based on the component attributes.

The study uses Ireland's rural landscapes as a case study. The Irish rural landscape has, and still is undergoing considerable change. Agriculture remains the largest rural land use with the Irish agri-food sector accounting for over half of the country's exports and almost 10% of the economy and employment (Teagasc, 2017). In many predominantly rural countries like Ireland, landscape images provide a visible representation of how the world sees the country and advertising campaigns such as Ireland's 'Origin Green' are used to promote global agri-food exports. As rural based sectors and the public goods they provide are heavily influenced by public policy, societal preferences in relation to rural areas are important. Landscape aesthetics, as one of the most visual and understandable public goods, is as a result, one of the most important drivers of support for the delivery of additional rural public goods.

The next section of this paper presents a review of models of landscape preference as a basis for model development. Section 3 then describes the data used in the analysis. The methodology is reviewed in section 4 while section 5 presents results and discussion. Finally, policy relevant conclusions are provided in section 6.

2. Models of Landscape Preferences

Increasingly, policy is focusing on the role of landscapes in the provision of ES, with landscape aesthetics being consistently included as an example of cultural ES. Many of these ES relate to the structure and composition of the landscape (Tscharntke *et al.*, 2005; Zhang *et al.*, 2007; van Berkel and Verburg, 2014; van Oudenhoven *et al.*, 2012). A variety of ecological/landscape indicators have been used to estimate the relationship between landscape characteristics and the potential for supply of ES (Kienast *et al.*, 2009; Burkhard *et al.*, 2010; van Berkel and Verburg, 2014), whilst integrative analytical approaches and models have been developed to assess trade-offs between ES and economic decisions (Vidal-Legaz *et al.*, 2013). Studies have also assessed the socio-cultural values of ecosystem services delivered by different landscape types (Hynes and Campbell, 2011; Martín-López *et al.* 2012).

While the value of the agricultural provisioning function of landscapes can be quantified using farm activity data, the quantification of the aesthetic value of landscapes remains a challenge. There are however studies that focus on particular cultural services that can be attributed to visual landscape characteristics, rather than the totality of potential ES. Such landscape preference studies use landscape photos to represent different types of landscapes (see for example Campbell *et al.*, 2006; Rambonilaza and Dachary-Bernard, 2007; Moran *et al.*, 2007; Hynes and Campbell, 2011). While the use of interviews with photo-elicitation and ranking enables researchers to identify landscape preferences and propose reasons underlying them, there are some criticisms of the reliability of evaluating aesthetic preference using photos. Bias in stated preferences may arise due to photo quality, light, weather, photo composition, and the number of photos presented (van Berkel and Verburg, 2014, Gill *et al.*, 2015). However, empirical results from numerous studies support the use of landscape images and other visual approaches combined with questionnaires, as a reliable method for the public evaluation of landscapes (Svobodova *et al.*, 2012; Häfner *et al.*, 2018).

2.1 Landscape Attributes

The concept of utilising landscape photographs as a proxy for landscape characteristics is commonplace in the literature (Kaltenborn and Bjerke, 2002; Arriaza *et al.*, 2004). While a photographic image does not represent the actuality of the experience of being in a landscape, there is a substantial literature that supports their use (Häfner *et al.*, 2018). According to Dramstad *et al.* (2006), preferences based on well-selected colour photographs of landscapes are similar to those made in the field. In this study, landscapes are decomposed into their individual attributes to examine the personal preferences for these attributes.

In a meta-analysis, van Zanten *et al.* (2014) created a typology of landscape attributes consisting of two levels. At the first level there are four attribute groups: human influence on agricultural landscapes, land cover attributes, landscape elements and biophysical features. The second level decomposes level one attributes into their various components, e.g. farm system, level of fragmentation, mountains etc.

Landscape scenes used in preference studies need to account for these different types of attributes. It is also important to distinguish the intensity of the various attributes. Häfner *et al.* (2018) found there was a higher preference for point attributes such as individual trees, as opposed to lines of trees or hedgerows, with a higher frequency preferred. The attributes extracted from landscape scenes for this analysis are also in line with those of De Ayala *et al.* (2012). They list the common attributes in landscape level discrete choice experiment studies as vegetation (e.g. trees, hedgerows), rural aspects (grassland, farm buildings), wildlife, water, cultural heritage (monuments, traditional farming), boundaries (stone walls and fences) and recreation (walking trails, fishing).

2.2 Judgements

Landscape has been described as the intersection between physical attributes of a place and individuals' perceptions of that place (Hanley *et al.*, 2009). Studies examining landscape values may use either expert judgement (objectivist approach), where the focus is on characterizing the landscape as an object, or personal preferences in the form of a survey (subjectivist approach), where the focus is on viewers' experiences of the landscape (Lothian, 1999; Tveit *et al.*, 2006). The objective approach considers landscape quality as an intrinsic attribute of the landscape, and requires an implicit understanding of human preferences for landscape. The subjectivist approach considers landscape quality as a human construct based on the interpretation of what is perceived as landscape through individuals' memories, associations and imagination. In the subjectivist approach, landscapes provide a means of understanding preferences of landscape viewers (Lothian, 1999). Within the field of landscape aesthetics, evolutionary theories and cultural preference theories have been developed to explain landscape perception and identify the factors and mechanisms that shape human preferences towards landscapes (Häfner *et al.*, 2018).

When using personal preferences, the context in which the survey is collected is important. Studies that are context specific make upscaling of results difficult (van Zanten *et al.*, 2014). Studies should therefore control for local context such as attitudes, location and demographics of the respondents. Education, for example, has been found to positively influence landscape preferences (Häfner *et al.*, 2018). However, in an assessment of landscape aesthetics, Frank *et al.* (2013) found few differences in the preference values across three different categories of respondents: the general population, experts and stakeholders.

The location in which a respondent lives can also influence their preferences. Meta-analysis results show that urban residents have a higher preference for forest and natural landscapes (van Zanten *et al.*, 2014). The landscape value of an area also includes the value placed on it by tourists and those not living in an area. Kirillova *et al.* (2014) examined the aesthetic judgement of tourists using semi-structured interviews and disaggregated their judgements into a total of nine dimensions. Zoderer *et al.* (2016) found that tourists' perceptions of landscape value vary with the land-use type and their socio-economic characteristics. In summary, some of the spatial, methodological and attribute choices in recent studies are presented in Table 1.

3. Methodological Framework

A range of indicators is required to comprehensively describe landscapes. The European Landscape Convention (ELC, 2000) for example integrates biophysical, cul-

Table 1. Choice of Landscape Attribute in Recent Studies.

Paper	Country	General scene or attributes	Scale (local or national)	Expert or survey
Häfner *et al.* (2018)	Germany	Attributes	Local	Stated preference survey (n=200)
Hermes *et al.* (2018)	Germany. 100m x 100m	Scene	National	Expert
Vidal-Legaz *et al.* (2013)	Spain. No spatial component	Scene	Local	Stated preference survey (n=226)
van der Jagt *et al.* (2014)	Scotland	Scene	Local	Preference matrix survey (n=100)
Zoderer *et al.* (2016)	Italy	Scene	Local	Stated preference survey (n=659)
Frank *et al.* (2013)	Germany	Scene	Local	Survey consisting of laymen and experts (n=153)
Bernués *et al.* (2019)	Multiple countries (Spain, Norway, Italy)	Attributes	Country regional/ provincial	Stated preference survey (n=1,044)
Dupras *et al.* (2018)	Canada (three regions; Saint-Jacque, Repentigny, and Montréal)	Attributes	Country regional	Survey consisting of laymen (n=250)

tural, social, and visual attributes of landscapes. In order to incorporate this integrated view and to combine public and expert opinion, Sowinska-Swierkosz and Chmielewski (2016) developed a methodological framework to identify Landscape Quality Objectives (LQOs) which include GIS analysis, quality assessments, social survey and expert value judgements.

This study also combines expert and public viewpoints in developing a model that links the visual attributes of landscapes (as defined by agricultural scientists) with individuals' landscape preferences, socio-demographic data and GIS analysis. The main benefit of using such a modelling approach is the ability to rank a landscape, using personal preferences derived from a survey but without the need to conduct surveys in every location. Similar to the use of value transfer approaches this means that the parameters of the preference model can be used to estimate rank orderings of landscapes without the need for further primary surveys providing time and monetary savings to both researcher and policy maker (Hynes *et al.* 2018).

In creating a formalised model of landscape preferences, it is first necessary to define the characteristics or attributes of landscapes. In doing so, choices are made (discussed previously), between broad holistic descriptions and more discrete, generalisable and quantifiable attributes of the landscape. The objective of this study to estimate a landscape preference model that is generalisable in an Irish context, thus a model of quantifiable landscape attributes is developed (equation 1) where:

$$Max\ U = \sum_i \beta_i \times l_i \qquad (1)$$

such that in maximising landscape preferences, or in economic terms utility from the landscape, U, a series of parameters β_i are estimated that indicate a level of preference for individual attribute l_i.

As a social science analysis, we are interested not only in the landscape attributes that are preferred but also preference heterogeneity across individuals or across groups of attributes , with personal characteristics and attitudes Z.

$$Max\ U_j = \Sigma_i\ \beta_i \times l_i \times Z_j \qquad (2)$$

Individuals' preference heterogeneity can be decomposed into different components. Beyond standard demographic characteristics in describing different groups, attitudinal factors are important (Swanwick, 2009). Appleton (1975) argues that individual preferences for landscapes depend upon the relationship between an individual and their environment, their experiences of the landscape, where individuals live and how they experience the landscape, while Howley (2011) finds heterogeneity in landscape preferences due to both demography and environmental orientations. The model should therefore account for the different drivers of preference variability (equation 3):

$$Max\ U_j = \Sigma_i\ \beta_i \times l_i \times Z_j\ (Demograhics, Attitudes, Location) \qquad (3)$$

In order to understand the structure of individuals' preferences for landscape attributes, survey respondents were first asked to rank preferences for individual photographs on a 6-point Likert scale from (1) 'not very highly' to (6) 'very highly'. While the ranking variable is potentially continuous over the range 1 to 6, discrete values were used for convenience. Treating the ranking as an underlying continuous variable, an Ordinary Least Squares (OLS) model, of the form:

$$Y_i = \beta' X_i + \varepsilon_i \qquad (4)$$

can be used for individual i, where Y_i^* is the dependent variable reflecting landscape preferences and X_i the explanatory variables and ε_i the error term.

As an alternative modelling strategy the dependent variable can also be treated as discrete and the ranking is ordinal, an ordered logit model is employed (Greene, 2004):

$$Y_i^* = \beta' X_i + \varepsilon_i \qquad (5)$$

for individual i, where Y_i^* is the underlying latent variable reflecting landscape preferences and X_i the explanatory variables and ε_i the error term.

Where there are six preference values 1,…,6, the following is the observed value of the dependent variable:

$$\begin{aligned} Y &= 1\ if\ 0 < Y_i^* < \mu_1 \\ Y &= 2\ if\ \mu_1 < Y_i^* < \mu_2 \\ \\ Y &= 6\ if\ \mu_5 < Y_i^* < \mu_6 \end{aligned} \qquad (6)$$

where Y is the preference value for the landscape image and μ, the vector of unknown threshold parameters that is estimated with the β vector. Since the dependent variable is an ordered, qualitative variable, we estimate the relationship between Y and X with an ordinal response model assuming a logistic distribution.

However, as respondents were asked to rank their preference level, the difference between ranking variables has a meaning and is consistent between values. Given that the difference between values has a meaning, utilising the ordered logit loses information in the estimation. Thus even though the survey respondents use discrete values in their judgement, a continuous framework is also employed to model preferences.

3.1 Landscape Attributes

In classifying landscape attributes, we move from preferences for individual photographs to preferences for a number of specific attributes . These include agricultural attributes, natural attributes, human-built non-agricultural attributes, topography and other attributes. Given the nature of the data, where there are repeated values for each survey respondent for each of the 30 attributes selected, we employ a fixed effect panel data ordered logit model (Greene, 2001, 2004), which has been widely used for attitudinal studies (Fairlie *et al.*, 2014), for the panel data continuous dependent variable:

$$Y_{ij} = \beta' Z_{ij} + u_i + \varepsilon_{ij} \tag{7}$$

and for the panel data ordered logit (equation 8):

$$Y_{ij}^* = \beta' Z_{ij} + u_i + \varepsilon_{ij} \tag{8}$$

where Z_{ij} represents the landscape characteristics' specific attributes, u_i represents the individual fixed effect and where the panel data variance component σ^2_{u} is also estimated.

3.2 Preference Heterogeneity

We move from person-specific preferences (X_i) in the cross-sectional ordered logit model to landscape attributes (Z_{ij}) in the panel data model. Interaction terms (taste-shifters) between the personal and the landscape attributes are incorporated in equation 9 so that the influence of personal characteristics on preferences can be examined:

$$XZ_{ij} = X_i \times Z_{ij} \tag{9}$$

to produce the following model:

$$Y_{ij}^* = \beta' Z_{ij} + \beta_1' XZ_{ij} + u_i + \varepsilon_{ij} \tag{10}$$

However, given that there are many landscape characteristic attributes, we combine the attributes into three aggregate characteristics representing natural, agricultural and human-built (non-agricultural) attributes:

$$Y_{ij}^{*} = \beta' Z_{ij} + \beta_1' X Z_{ij}^{nature} + \beta_2' X Z_{ij}^{agri} + \beta_3' X Z_{ij}^{human} + u_i + \varepsilon_{ij} \tag{11}$$

4. Data

To assess the preferences of the public in relation to landscape attributes, a nationally representative survey[1] of 430 individuals aged 15+ was conducted in Ireland in 2010 (Howley, 2011).

The survey contained a number of components including:

- personal information and demographic characteristics
- preferences and attitudes to agriculture, the environment and natural resources
- landscape characteristics

This demographic and environmental information is later interacted with the respondents' locations to generate 'taste-shifters'. The initial parts of the survey also elicited responses in relation to the respondent's environmental attitudes and orientations. Respondents were then asked to indicate their preferences (from 1 - not very highly ranked, to 6 – highly ranked) at an aesthetic level, for a range of photographs of rural landscapes. Respondents were asked to make full use of the ranking scale and to give the highest ranking to their most preferred landscapes.

4.1 Landscape preferences

To ascertain landscape preferences, 50 photographs of rural landscapes with a variety of different characteristics were presented to survey respondents. The photos used were selected from a database of 1,000 photos from the national agricultural development authority. They were selected in collaboration with colleagues to attempt to be representative of rural settings, incorporating extensive farming landscapes along with intensive farming landscapes. As the process of selecting images to represent the range of landscapes is relatively arbitrary, it is possible that a different set of photos would produce different outcomes. In order to improve reliability, photos were selected that had similar weather and light conditions. To ensure a representative sample, the survey was collected at different times of the day over the summer months.

Tables 2 and 3 respectively report the six most preferred and the six least preferred landscapes. The most obvious conclusion is that there is a higher preference for water and coastal features in the landscape. Similarly, the presence of animals or heritage features is important. On the other hand, the least preferred landscapes contain human-built features such as motorways or wind turbines and also contain disorder such as flooding or unmanaged scrub and grassland or contain harvested peat bogs. In the Data Annex, we report the preferences for all photographs. Beyond the six most preferred, the next cohort of photos represents well-managed pastoral agriculture scenes and broadleaf forests/trees. Those photos ranked just above the least preferred landscapes, represent intensive cereal and horticultural farming on the one hand, as well as marginal scrubland, along with conifer forest.

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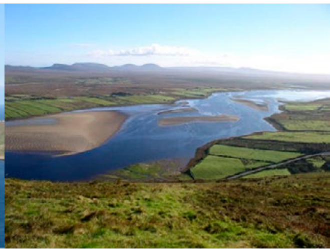
[1] Quota sampling and survey validation are reported in Howley (2011).

Table 2. Most Preferred Landscapes (photo numbers correspond to ranks in Table A1-Data Annex).

1. Coastal image of sea and headland

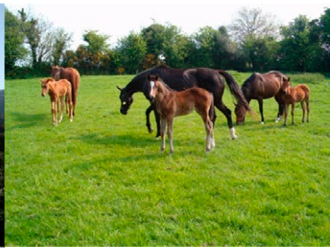
2. Aerial photo of a river estuary



3. Coastal cliffs

4. Lake in rural setting

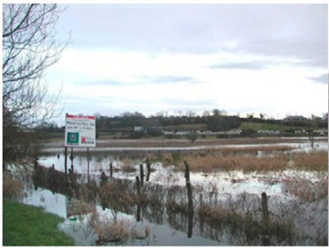
5. Horses in field



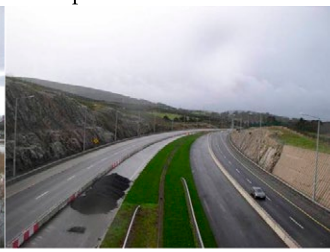
6. Large tree next to castle ruin in field

Table 3. Least Preferred Landscapes (photo numbers correspond to ranks in Table A1).

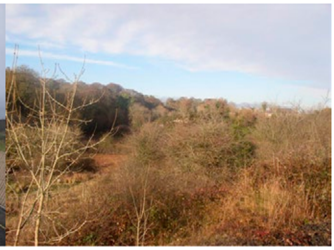
50. Flooded farmland



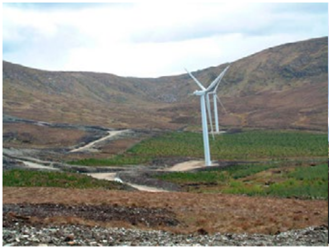
49. New motorway cutting through landscape



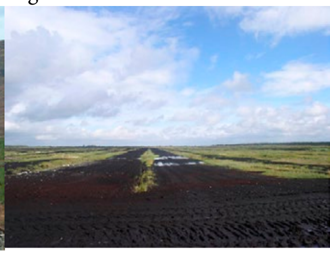
48. Scrubland next to woodland



47. Barren hillside with wind turbine



46. Landscape of industrial bogland



45. Trees and scrubland with blue horizon

4.2 Landscape Attributes

This study took a relatively simple approach to classifying attributes, attempting to score the significant presence of an attribute, rather than trying to grade the photo for the degree of importance of a particular attribute. Thus the presence of an attribute that was immediately visible on a quick inspection was scored as 1, as it was felt that these reflect the dominant attributes of an image. If an attribute was not immediately visible on a quick inspection, the attribute was scored as 0. Thus while each photograph has a specific rating of 1-6, we have added additional dummy attributes or explanatory variables for each photo. In the dataset, it is expressed as a separate line for every attribute, with 1 for the presence of the attribute and a 0 otherwise. It thus appears as a panel, with personal characteristics invariant over the panel and landscape attributes varying over the panel.

Table 4 describes the share of ratings from 'not very highly' (1) to 'very highly' (6) for these landscape attributes based on the original landscape rankings. Ranking these attributes on the basis of where they appear in landscapes with 'very highly' ranked preferences, we note the higher preferences for the attributes lakes, cliffs, horses, water, monuments, hedgerows and Connemara-type landscape which can be collectively described as 'landscape descriptions'[2]. The next highly ranked attributes can be described as 'pastoral agriculture' attributes such as livestock and pasture. At the other end of the preference scale, anthropogenic features such as wind turbines, fencing and problems like flooding and rough grazing landscapes (including gorse) have the lowest preference rankings.

4.3 Environmental Attitudes

To gain a deeper understanding of how environmental attitudes might influence landscape preferences, the survey instrument included questions relating to preferences for landscapes as a provider of ES (in addition to its aesthetic or intrinsic value), or as a provider of food and fibre, and questions relating to negative attitudes towards the environment in general. The resulting environmental attitudes were aggregated using factor analysis as described by Howley (2011), resulting in three underlying factors that accounted for 61% of the underlying variation in responses to the attitudinal statements, namely 'multifunctionalist', 'productivist' and 'environmental apathy'. These factors are used in the models as explanatory variables.

4.4 Spatial heterogeneity

Given the heterogeneity of landscapes, spatial heterogeneity of preferences for attributes may exist. Previous approaches to account for this used distance decay, where WTP is a function of distance between residence and the site being valued (Hanley *et al.*, 2003) or where area-based approaches improve basic distance decay using a radial analysis to model WTP as a function of both distance and quantity of the ES (Granado-Díaz *et al.*, 2020). The distance decay function may also be impacted by the presence of substitute environmental attributes (Jørgensen *et al.*, 2013). Use and non-use values are also impact-

[2] Connemara is a remote, scenic, rugged landscape in the west of Ireland.

Table 4. Landscape Attribute Summary Statistics showing shares of preference rankings from not very highly (1) to very highly (6).

Attribute	1	2	3	4	5	6
Lakes	0.04	0.05	0.09	0.16	0.21	0.46
Cliffs	0.07	0.06	0.07	0.13	0.22	0.44
Horses	0.1	0.03	0.09	0.17	0.2	0.41
Water	0.06	0.08	0.13	0.15	0.23	0.36
Monuments	0.09	0.08	0.11	0.18	0.24	0.3
Hedgerows	0.07	0.07	0.15	0.19	0.24	0.28
Connemara-type landscape	0.04	0.19	0.16	0.17	0.19	0.25
Pasture	0.1	0.09	0.15	0.2	0.22	0.24
Sloping	0.11	0.12	0.16	0.18	0.21	0.23
Stonewalls	0.11	0.1	0.15	0.21	0.22	0.22
Cattle	0.13	0.1	0.15	0.2	0.21	0.21
Mountains	0.16	0.17	0.16	0.15	0.16	0.2
Neat Agricultural Landscape	0.1	0.13	0.16	0.2	0.21	0.2
Sheep	0.11	0.11	0.16	0.21	0.22	0.2
Green	0.11	0.13	0.17	0.19	0.2	0.2
Blue Sky	0.15	0.17	0.17	0.17	0.17	0.18
Bog (peatland)	0.15	0.16	0.16	0.17	0.17	0.18
Sunny	0.14	0.17	0.17	0.18	0.17	0.17
Native Trees	0.18	0.16	0.16	0.17	0.17	0.17
Old Buildings	0.1	0.14	0.17	0.21	0.21	0.17
Flowers	0.11	0.17	0.19	0.21	0.19	0.14
Flat	0.16	0.19	0.18	0.17	0.16	0.14
Cars and Machinery	0.22	0.2	0.17	0.15	0.14	0.13
Crops	0.13	0.17	0.19	0.21	0.18	0.12
Turf	0.18	0.23	0.19	0.16	0.1	0.12
Brown	0.19	0.21	0.18	0.16	0.14	0.12
Yellow	0.16	0.16	0.2	0.2	0.17	0.12
Unmanaged Landscape	0.19	0.21	0.2	0.16	0.13	0.12
Conifer Trees	0.17	0.18	0.21	0.18	0.15	0.11
Other Buildings	0.18	0.2	0.2	0.17	0.15	0.1
Gorse	0.26	0.21	0.18	0.14	0.12	0.09
Fencing	0.4	0.21	0.12	0.09	0.09	0.09
Turbine	0.21	0.21	0.19	0.18	0.13	0.08
Flooding	0.58	0.27	0.1	0.03	0.01	0.01

ed by distance (Jørgensen *et al.*, 2013). For option value related reasons, non-users may prefer an improvement in local landscapes (Hanley *et al.*, 2003). We also attempt to capture some of the spatial heterogeneity of preferences by using an urban-rural classification based on the respondent's location.

Summary statistics for a variety of taste shifters are presented in Table 5. These are categorised in terms of city, town and rural dwellers and include characteristics of individ-

Table 5. Summary Statistics of Personal Characteristics and Environmental Preferences used as Taste Shifters.

Personal Characteristic	City	Town	Rural	Total
Has a Child (p)	0.365	0.352	0.424	0.379
Aged Under 30	0.256	0.246	0.250	0.251
Aged 30-50	0.410	0.423	0.394	0.409
Aged 50-60	0.103	0.092	0.152	0.114
Aged 60+	0.231	0.239	0.205	0.226
University Educated	0.442	0.254	0.242	0.319
Believes landscape is important in choosing where to live	0.186	0.268	0.424	0.286
Satisfied with area in which they live	0.147	0.113	0.106	0.123
Believes surrounding landscape is of high quality	0.487	0.599	0.689	0.586
Higher Social Class	0.763	0.634	0.606	0.672
Farming Background	0.231	0.394	0.614	0.402
Care about Conservation	0.301	0.359	0.432	0.360
Concerned about the environment	0.186	0.324	0.242	0.249
Factor Loading: Multifunctionalist	-0.114	0.128	-0.002	0.000
Factor Loading: Environmental Apathy	-0.036	0.114	-0.081	0.000
Factor Loading: Productivist	-0.173	0.073	0.126	0.000

ual respondents, along with their environmental attitudes, illustrating the degree to which preferences vary depending on where respondents live. Specifically, social and demographic information includes respondent's age range as a continuous variable with values of 1 (under 30) to 4 (60+), with dummy variables indicating respondents' education level and whether they have a child. Two social groups were created; the first includes manual workers and unemployed individuals, whereas professional and managerial workers were classified in the second social class (high social class). In addition, respondents or family members who are involved in farming were compared with those without a farming background. Similarly, dummy variables were created to control for the importance of landscape in choosing where to live, the level of respondents' satisfaction with respect to the area in which they live, the quality of surrounding landscape, and their concern about the environment and conservation.

5. Results

The results of the models of landscape attribute preferences are considered separately for the ordinal logit and the continuous dependent variable panel and pooled OLS models. The influence of personal characteristics on preferences, using taste-shifters (interaction terms) between the personal characteristics and landscape types are also presented and discussed.

In Table 6, the coefficients for the landscape attributes are reported in terms of natural, agricultural and human-built features, as well as other general attributes such as colour and unmanaged landscapes. Although there are many variables, the OLS specification

Table 6. Coefficients of Panel and Pooled Ordered Logit Model and Panel and Pooled OLS Models for Landscape Attributes.

	Panel Ordered Logit Model		Pooled Ordered Logit Model		Panel OLS Model		Pooled OLS Model	
Explanatory Variables	Beta	SD	Beta	SD	Beta	SD	Beta	SD
Natural Landscape Characteristics								
Connemara type landscape	1.397*	0.419	1.454*	0.118	1.005*	0.073	0.98*	0.075
Lakes	0.988*	0.531	1.004*	0.149	0.67*	0.096	0.662*	0.094
Cliffs	1.033*	0.294	1.015*	0.083	-0.039	0.035	0.592*	0.052
Water	0.628*	0.202	0.632*	0.056	0.393*	0.041	0.383*	0.036
Flowers	0.37*	0.213	0.383*	0.058	0.214*	0.045	0.258*	0.038
Bogland	0.35*	0.016	0.349*	0.016	0.189*	0.01	0.213*	0.01
Sloping	0.193	0.182	0.165*	0.05	0.117*	0.033	0.11*	0.032
Native Trees	0.034	0.138	0.061	0.038	0.066*	0.03	0.057*	0.025
Mountains	-0.188	0.26	-0.136*	0.072	-0.095*	0.049	-0.097*	0.046
Flat	-0.389*	0.153	-0.254*	0.051	-0.113*	0.027	-0.138*	0.033
Conifer Trees	-0.547*	0.314	-0.435*	0.087	-0.262*	0.064	-0.25*	0.057
Gorse	-0.806*	0.269	-0.639*	0.08	-0.34*	0.047	-0.365*	0.052
Flooding	-2.409*	0.482	-2.375*	0.134	-1.681*	0.086	-1.708*	0.085
Agricultural Landscape Characteristics								
Horses	0.533	0.467	0.6*	0.132	0.26*	0.084	0.26*	0.082
Neat Agricultural Landscape	0.424*	0.232	0.362*	0.067	0.167*	0.048	0.198*	0.043
Pasture	0.184	0.176	0.166*	0.049	0.115	0.194	0.109*	0.032
Crops	-0.375	0.274	-0.368*	0.093	-0.249	0.298	-0.246*	0.06
Cut-Silage	-1.245*	0.591	-1.145*	0.169	-0.755	0.65	-0.688*	0.11
Human Landscape Characteristics								
Monuments	0.947*	0.294	0.874*	0.096	0.618*	0.321	0.568*	0.061
Hedgerows	0.347	0.302	0.291*	0.095	0.297	0.329	0.257*	0.061
Stonewalls	0.117	0.309	0.109	0.095	0.123	0.338	0.123*	0.062
Old Buildings	0.026	0.3	0.036	0.094	0.073	0.328	0.082	0.06
Turf	-0.122	0.397	-0.33*	0.125	-0.099	0.434	-0.26*	0.079
Turbine	-0.271	0.326	-0.429*	0.105	-0.151	0.355	-0.284*	0.068
Other Buildings	-0.167	0.212	-0.395*	0.075	-0.1	0.228	-0.273*	0.048
Cars and Machinery	-0.382*	0.225	-0.509*	0.074	-0.285	0.244	-0.393*	0.047
Other Landscape Characteristics								
Yellow	1.019*	0.388	0.905*	0.107	0.646	0.428	0.564*	0.069
Green	0.129	0.155	0.138*	0.042	0.091	0.171	0.092*	0.027
Unmanaged Landscape	0.072	0.257	-0.051	0.074	0.035	0.283	-0.062	0.048

	Panel Ordered Logit Model		Pooled Ordered Logit Model		Panel OLS Model		Pooled OLS Model	
Brown	-0.368*	0.204	-0.325*	0.056	-0.261	0.226	-0.238*	0.036
Constant					3.686	0.276	3.674	0.061
Cut Point 1	-2.623	0.258	-2.548	0.102				
Cut Point 2	-1.435	0.256	-1.378	0.096				
Cut Point 3	-0.202	0.256	-0.175	0.095				
Cut Point 4	1.105	0.256	1.102	0.095				
Cut Point 5	2.531	0.256	2.508	0.096				
Sigma Squared (u)					0.358			
Sigma Squared (e)					1.149		1.168	
Rho					0.089			
							0.223	
Pseudo R^2			0.079					
Within					0.080			
Between					0.866			
Overall					0.240			
N	20600.000		20600.000		20600.000		20600.000	
Number of Groups	50.000				50.000			

is satisfactory from a multi-collinearity perspective, as the VIF (Variance Inflation Factor) for all values is less than 10 (Kassie *et al.*, 2008). In comparing the models, it is evident that virtually all of the coefficients are within the significance limits of the panel data ordered logit model, so that the models do not in general have substantial differences in their coefficients. We note however that the confidence intervals are wider for the panel data ordered logit than for the pooled version of the model or for the panel and pooled OLS specifications, reflecting perhaps that we utilise less of the information in the panel ordered logit model estimation than the in the pooled version or continuous dependent variable OLS models. Unsurprisingly the Breusch-Pagan Lagrangian multiplier finds the fixed effects insignificant. Therefore, we focus on the OLS pooled model for the discussion and for the introduction of the taste shifter interactions. Overall, the pseudo R^2 is 24%, representing relatively large unexplained heterogeneity of landscape preferences.

Of the natural attributes, the Connemara type landscape, which represents a remote rugged mountainous area, has the highest positive coefficient. This is followed by preferences for cliffs, lakes and water as landscape attributes. Landscapes with flowers, native trees, bog (peat), sloping land and native trees have the next highest coefficients. Landscapes with flooding have the lowest coefficient of the natural landscapes. The mountain landscape has an unexpected sign, but it shares considerable information with the Connemara type landscape.

In relation to the agricultural landscape attributes, the presence of horses has the greatest positive significance, followed by neat agricultural land and pasture, whilst crops and cut-silage have negative coefficients. In relation to human-built landscape attributes, the presence of monuments has the highest positive and significant coefficient. Indeed, it has the second highest coefficient overall. Human-built landscape attributes associated with farming such as hedgerows and stone walls have the next highest coefficient, followed by old buildings. Meanwhile negative preferences are observed on average for industrial or mechanised objects or activities such as wind turbines, cars and industrial turf-cutting. Also, yellow and green colours (conditional on other attributes) are positive while unmanaged rural landscapes have a negative coefficient. This preference for managed agricultural landscapes highlights the frequent mismatch between aesthetic preferences and ecological diversity (Gobster *et al.*, 2007). Interestingly, amongst the least preferred landscapes are unmanaged (potentially biodiversity-rich) landscapes, perhaps reflecting evolutionary processes that favour landscapes that have a greater possibility of providing food and shelter.

5.1 Taste Shifters

We interact personal characteristics and attitudes with preferences for natural, human built and agricultural attributes to form taste shifters. Interaction terms between the personal characteristics and landscape types allow us to examine the influence of personal characteristics on preferences and are a means of controlling for observed heterogeneity in preferences within the model. In interacting personal characteristics and landscape characteristics, we group characteristics into natural, human and agricultural characteristics, thus reducing the degrees of freedom. Reflecting the fact that attributes have both positive and negative signs in Table 8, we break up the groups into positive and negative coefficients.

We combine 15 personal characteristics with six different types of landscape attribute. Given that there are 90 combinations of these variables with potentially overlapping information and multi-collinearity, we use a Principal Component Analysis (PCA) to reduce the dimensionality, and present the detailed results in Table A2 Data Annex. Although there are 25 factors with an Eigenvalue of more than 1, accounting for 75% of information, on the grounds of parsimony, we select only those with an Eigenvalue of 2 or higher (Hair *et al.,* 2010). To aid the interpretation of these, we employed a method known as Component Rotation (Bechtold and Abdulai, 2014). This method was used to distinguish between components and to facilitate the interpretation of components (see Table A3 Data Annex for detail on rotated components). The widely applied Varimax Rotation (Abdi and Williams, 2010) was also employed. Table 7 presents the interpretation of the principal components and the coefficients of the pooled OLS model interacted with the taste shifters, referencing both the socio-economic characteristics and the landscape attribute group associated with the principal component. For half of these principal components, a single socio-economic characteristic was found to be dominant combined with four landscape attribute groups, positive natural, positive agricultural, positive human and negative natural, highlighting a coherent association with different landscape attribute types.

Taste shifters capture preference heterogeneity relative to observed characteristics. For example, PC1 corresponds to a negative coefficient on agricultural landscapes for high social class (professional and managerial workers) city dwellers. A positive coefficient on this component suggests a less negative preference for crops and cut-silage than other groups. PC2 refers to the preferences of town dwellers for human and agricultural characteristics that have a positive coefficient. Here, a positive coefficient indicates a higher preference for these attributes than the general population. PC3 relates to preferences for natural attributes,

Table 7. Coefficients of Pooled OLS Model interacted with Taste Shifter Principal Components.

Explanatory Variables				
Landscape Characteristics Interactions	Interpretation	Landscape attributes	Coefficient	Standard Error
PC1	High social class city dwellers	na	0.038	0.005***
PC2	Town dwellers	ph pa	0.019	0.007**
PC3	Older, town dwellers and higher social class	nn	-0.031	0.008***
PC4	Higher educated city dwellers with children	nh	-0.042	0.006**
PC5	City dwellers	ph pa	-0.015	0.006***
PC6	Town dwellers	pa, nh, na	0.015	0.006***
PC7	Satisfaction of area	pn, ph, pa, nn,	-0.030	0.004***
PC8	Environmentally concerned	nh	-0.035	0.006***
PC9	Importance of landscape in choosing where to live	pn, ph, pa, nn,	0.040	0.005***
PC10	Farming background	pn, ph, pa, nn,	0.005	0.005
PC11	Multi-functional agriculture	pn, ph, pa, nn,	-0.048	0.005***
PC12	Concerned about the environment	pn, ph, pa, nn,	-0.015	0.006**

Note: pn – natural attributes (positive sign); ph – human attributes (positive sign) ; pa – agricultural attributes (positive sign); nn – natural attributes (negative sign); nh – human attributes (negative sign); na – agricultural attributes (negative sign).

where higher social classes, older respondents and those living in towns have lower than average preferences for these attributes. There is a similar impact on human attributes (PC4) with a negative score for higher-educated city dwellers or those with children. City dwellers in PC5 have lower than average preferences for human and agricultural attributes, while for PC6, town dwellers have higher preferences for both positive and negative agricultural attributes and more negative human attributes than average. In PC8, those with environmental concerns and landscape views have a lower preference for negative human aspects.

The remaining principal components all relate to individual socio-economic characteristics interacted with the four sets of attributes highlighted above. Those that place a high ranking on the importance of landscape in choosing where to live have higher landscape preferences than average, while those that are concerned about the environment or with multi-functional attitudes have lower preferences.

In summary, grouping the landscape attributes into natural, agricultural (including human built) and non-agricultural human-built attributes, the results show positive associations with natural attributes such as cliffs, mountainous landscapes, landscapes with water and native trees, neat/managed agricultural landscapes and traditional human-built features such as stone walls and planted hedgerows. The results, as expected, show negative associations with events such as flooding, unmanaged landscapes, industrial turf cutting and mechanised features.

There is significant preference heterogeneity however with different groups favouring or disfavouring different attributes. An urban-rural classification used to capture the spatial heterogeneity of preferences (based on the respondents' locations) showed that those living in urban areas feel they have a lower quality of surrounding landscape compared to rural areas. Unsurprisingly those that have chosen to live in a rural landscape place the highest value on this type of landscape, while farmers have the highest preference for agricultural landscape attributes. Urban dwellers are more indifferent towards natural and farming landscapes. Underlying eco-centric attitudes are also important drivers.

6. Conclusions

This study adopted an attribute choice framework to disentangle individual preferences for a holistic image of landscape photographs into preferences for specific attributes of that landscape, and subsequently used these attributes in landscape preference models to relate societal preferences to quantifiable landscape attributes. The study further investigated whether individuals' characteristics interact with landscape attributes and how these interactions ultimately affect public preferences for landscapes.

This paper adopts a middle-ground approach between the methods found in the literature for landscape preference modelling. On the one hand, it is ambitious in relation to the range of landscape attributes as in the case of Schirpke *et al.* (2016) or Bernués *et al.* (2019), but is less ambitious in focusing on preference attributes rather than willingness to pay, as in the stated preference valuation literature. It also extends the work of Schirpke *et al.* (2016) by considering the preference heterogeneity for specific landscape attributes. Although unobserved heterogeneity is not considered in this study, the variety of observed heterogeneity incorporated may be more useful for policy and from a simulation modelling perspective. Ultimately, the model results highlight differences in how people with different attitudes and characteristics rank landscape features. The impact of taste shifters on various groups illustrates the heterogeneity in rankings.

As noted by Hynes *et al.* (2011) the attribute based approach to landscape preferences allows the researcher to examine the general trade-offs which society is willing to make between different attributes of the countryside. On the other hand, modelling landscape preferences based on landscape photos, such as in Howley's (2011) study, is useful if the researcher is interested in understanding preferences for the wider landscape. The approach adopted here is particularly useful where one is interested in the utility gained or lost through a policy that may cause only incremental changes in the landscape or impact on only a small number of attributes. Interacting personal characteristics as taste shifters can help us to understand local preferences if the characteristics of the local population differ. The analysis does have the limitation of not being able to identify local preferences in terms of sense of place or relational value. Qualitative studies or localised surveys are needed to understand these more nuanced perspectives (Pérez-Ramírez *et al.*, 2019; Vannier *et al.*, 2019; Wartmann and Purves, 2018).

Moving from a holistic view of landscapes to analysing preferences for specific attributes of landscapes allows for further applications particularly in the area of simulation. Being able to assess preferences for an individual attribute makes it possible to extrapolate the preference ranking of a landscape in an area that has not been ranked directly. It is important to note however that the method adopted in this paper is based on the assumption that the sum of the singular landscape element's preference scores equates to the preference ranking of the landscape as a whole. That simplifies the way in which humans value the environment and should be considered as a limitation of our study. As such, the method is more appropriate when there are only a limited number of attributes to be considered in a given landscape.

Human-built landscape characteristics such as stone walls and hedgerows are found to be positively associated with the preference rankings of photos in this study. Thus, future land-use changes and landscape development plans should promote the aesthetic role of stone walls and hedgerows and prioritise their conservation. Similarly, the recognition of the high aesthetic value that the public places on well-managed/neat agricultural landscapes provides policy justification to incentivise farmers to maintain these public goods in future agri-environmental schemes.

The results presented in this paper provide evidence of the preferences of a diverse range of individuals across a number of characteristics that should be of assistance to policy makers attempting to maximise the benefit for society from rural landscapes. The model developed here provides information for decision-makers to examine whether a proposed policy change involving one or more landscape attributes will have a positive or negative impact across the population, while also allowing for more targeted policy formation by disaggregating the population into different preference cohorts.

The approach adopted in this paper facilitates the creation of a formalised model of landscape preferences based on the component attributes. Decomposing complete landscape images into quantifiable attributes is a common feature of preference studies and can help bridge the gap between the GIS literature and landscape analysis. The latter typically takes quantifiable landscape attributes from GIS datasets to create typologies of different types of landscapes. Meanwhile the former assesses societal preferences for holistic images. Our methodology can further allow for the application of societal preferences to quantifiable datasets of landscape attributes, rather than using expert judgement as is currently the case.

The approach developed in this study therefore, has implications for planners for Landscape Character Assessments (LCA) that often utilise a broad expert knowledge approach to developing LCA maps, which may under/over estimate the value of various landscape attributes. Future work will apply this methodology in a GIS landscape database to re-assess LCAs from a societal rather than an expert point of view. Future work should also test for the existence of spatial dependence and use spatial regression methods to examine spatial heterogeneity in more detail.

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Data Annex: Assessing population landscape characteristic preferences using disaggregated attributes for rural landscapes

Table A1. Ranking of Photos by Survey Participants.

Rank	Photo Description
1	Coastal image of sea and headland
2	Aerial photo of a river estuary
3	Coastal cliffs
4	Lake in rural setting
5	Horses in field
6	Large tree next to castle ruin in field
7	Rolling hills, with conifers and well-kept fields
8	Copper beech tree in parkland
9	Sandy Beach
10	Stream flowing through Deciduous forest
11	Patchwork quilt of fields and river
12	The Rock of Cashel Historic Monument
13	Rich farmland and hillside in background
14	Remote hillside, with trees
15	Large rock in field on hillside
16	Field of sheep in lowland good grass and stone walls
17	Hillside of bluebells and deciduous trees
18	Remote (Connemara) mountainous landscape
19	Traditional farm building
20	Forest track in deciduous trees
21	Stonewalls with neat field of sheep
22	Stonewall with cows in field and trees on hillside
23	Dairy cows in field
24	Large field after silage cut
25	Stonewalls with neat field of oil seed rape
26	Sheep in front of traditional farmhouse
27	Statue of harpist in rural village
28	Hilly Woodland and Trees
29	Large field of cereal crops
30	Wildflower in field of ferns
31	Hillside of conifer trees
32	Trees and field of rushes
33	Mature forest
34	Rows of horticulture crops in field
35	Neat rows of cereal crops
36	Rocky mountain with extensive agriculture
37	Tillage field after harvest with blue sky
38	Mechanical cutting of turf from bog
39	Hillside of conifer

Rank	Photo Description
40	Reeds and scrubland
41	Marginal land with trees in background
42	Large horticulture field
43	Barren bogland
44	Heather in bogland
45	Trees and scrubland with blue horizon
46	Landscape of industrial bogland
47	Barren hillside with wind turbine
48	Scrubland next to woodland
49	New motorway cutting through landscape
50	Flooded farmland

Table A2. Principal Component Analysis.

Principal Component	Eigenvalue	Cumulative Proportion of Variance
P. Component 1	8.79458	0.0977
P. Component 2	6.75435	0.1728
P. Component 3	5.62239	0.2352
P. Component 4	4.78296	0.2884
P. Component 5	4.50848	0.3385
P. Component 6	3.63383	0.3789
P. Component 7	3.32083	0.4157
P. Component 8	2.9566	0.4486
P. Component 9	2.75087	0.4792
P. Component 10	2.55781	0.5076
P. Component 11	2.43572	0.5346
P. Component 12	2.2716	0.5599
P. Component 13	1.72736	0.5791
P. Component 14	1.71575	0.5981
P. Component 15	1.64843	0.6165
P. Component 16	1.49928	0.6331
P. Component 17	1.44856	0.6492
P. Component 18	1.39257	0.6647
P. Component 19	1.34819	0.6797
P. Component 20	1.27425	0.6938
P. Component 21	1.15625	0.7067
P. Component 22	1.09155	0.7188
P. Component 23	1.08972	0.7309
P. Component 24	1.07077	0.7428
P. Component 25	1.03101	0.7543

Table A3. Rotated components (orthogonal varimax) with loading < 0.3.

Correlations	Type	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12
Environmental Apathy	pn												
Multifunctional	pn											0.4372	
Productivist	pn												
Child	pn												
Age	pn												
University Educated	pn												
Social Class	pn												
City	pn												
Town	pn												
Farming Background	pn										0.5274		
Importance of Landscape in choosing where to live	pn									0.5221			
Satisfaction of Area	pn							0.5158					
Quality of Surrounding Landscape	pn												
Concerned about the environment	pn												0.5444
Care about Conservation	pn												
Environmental Apathy	ph												
Multifunctional	ph											0.5415	
Productivist	ph												
Child	ph												
Age	ph												
University Educated	ph												
Social Class	ph												
City	ph					0.5363							
Town	ph		0.5323										
Farming Background	ph										0.3401		
Importance of Landscape in choosing where to live	ph									0.3549			

Correlations	Type	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12
Satisfaction of Area	ph							0.3808					
Quality of Surrounding Landscape	ph												
Concerned about the environment	ph												0.3469
Care about Conservation	ph												
Environmental Apathy	pa												
Multifunctional	pa											0.4315	
Productivist	pa												
Child	pa												
Age	pa												
University Educated	pa												
Social Class	pa												
City	pa					0.3594							
Town	pa		0.3358				0.3134						
Farming Background	pa										0.4866		
Importance of Landscape in choosing where to live	pa									0.4983			
Satisfaction of Area	pa							0.4935					
Quality of Surrounding Landscape	pa												
Concerned about the environment	pa												0.4943
Care about Conservation	pa												
Environmental Apathy	nn												
Multifunctional	nn											0.4412	
Productivist	nn												
Child	nn												
Age	nn			0.4426									
University Educated	nn												
Social Class	nn			0.3384									
City	nn												
Town	nn			0.3778									

Correlations	Type	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12
Farming Background	nn										0.3769		
Importance of Landscape in choosing where to live	nn									0.3979			
Satisfaction of Area	nn							0.4121					
Quality of Surrounding Landscape	nn			0.3442									
Concerned about the environment	nn												0.401
Care about Conservation	nn												
Environmental Apathy	nh								-0.3381				
Multifunctional	nh								0.37				
Productivist	nh												
Child	nh				0.3044								
Age	nh				0.3886								
University Educated	nh				0.3016								
Social Class	nh				0.4032								
City	nh				0.4638								
Town	nh						0.3459						
Farming Background	nh												
Importance of Landscape in choosing where to live	nh								0.4122				
Satisfaction of Area	nh												
Quality of Surrounding Landscape	nh												
Concerned about the environment	nh								0.4373				
Care about Conservation	nh								0.3908				
Environmental Apathy	na												
Multifunctional	na												
Productivist	na												
Child	na												
Age	na												
University Educated	na												

Correlations	Type	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Comp10	Comp11	Comp12
Social Class	na	0.3004											
City	na	0.4851											
Town	na						0.56						
Farming Background	na												
Importance of Landscape in choosing where to live	na												
Satisfaction of Area	na												
Quality of Surrounding Landscape	na												
Concerned about the environment	na												0.3044
Care about Conservation	na												

Note: pn – natural attributes (positive sign); ph – human attributes (positive sign) ; pa – agricultural attributes (positive sign); nn – natural attributes (negative sign); nh – human attributes (negative sign); na – agricultural attributes (negative sign);