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Assessment Method for Agricultural Landscapes through the Objective Quantification of Aesthetic Attributes

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ABSTRACT: This paper presents a new approach for assessing agricultural landscapes based on mixture methods and the study and definition of aesthetic attributes as lines, forms, texture, spatial composition, scale and color as they are the closest to human perceptual aesthetic attributes. A set of variables capable of quantifying those attributes in a simple, objective and systematized way will be proposed. They are related with physical dimensions such as length, radium, angle, surface or brightness. People preferences for a specific type of agricultural landscape have been collected and different regression models between preferences and variables capable of quantifying attributes have been tried. The optimal model, explaining 82.3% of the variance in population preferences, selects 41 variables, adopts a linear structure and identifies the color as the most relevant attribute on population preferences and, inside it, green brightness as the most positive influencing variable on preferences being referred to red gamma the most influencing negative one.

Key words: Landscape preferences, Landscape valuation method, Landscape assessment

INTRODUCTION

Nowadays, discussions about the optimal method to assess landscapes cannot ignore the European Landscape Convention (ELC) and the principles there established related to the active resource management, to public participation in the landscape management, to the assumption of the territorialized character not only linked to its singularity and to the necessary consideration of perception. In order to satisfy requirements from ELC, some authors have supported mixture methods (Daniel, 2001), as they have predictive and explicative qualities and include population and their preferences since the preliminary stages of development, and many specific applications have been developed (Arriaza *et al.*, 2004; Real *et al.*, 2000; Schirpke *et al.*, 2013; Wherrett, 2000). Furthermore, mixture methods are more operable than direct ones and they provide the unequivocal consideration of preferences, in opposition to indirect ones.

Recent literature has studied attributes and variables able to characterize landscape inside mixture methods and although there are authors who advocate using environmental, aesthetic, psychological attributes or even combinations between them, the category of attributes closest to perceptual processes is the aesthetic one (Gobster and Chenoweth, 1989). Models using aesthetic attributes ensure a greater universality (Daniel and Boster, 1976), making them the best for studying non-singular landscapes.

Among methodologies referred to aesthetic attributes, those carried out by Smardon *et al.* (1979), later concreted by other authors such as García *et al* (2003), García *et al* (2006) or García-Moruno *et al* (2010), which are based on six aesthetic attributes: color, lines, forms, texture, spatial composition and scale, are the most frequently applied. Those six attributes have the advantage of being involved in the human mental perception process, as several studies have demonstrated their individualized and independent perception and their link with the earliest and objective stages of perception (Lewis *et al.*, 2011; Moutoussis and Zeki, 1997a; 1997b). Furthermore, the greater universality of those attributes, all of whom can be identified and measured in any landscape, makes them optimal to develop methodologies respectful to the territorialized character of landscape, which requires defining specific tools for every landscape avoiding universal hierarchies (Bearlant, 2010). But despite their

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advantages, those six attributes have traditionally been criticized for its complicated handling and interpretation, and even for the lack of objective procedures to be measured (Zhao *et al.*, 2013). Moreover, the aforementioned studies are specially oriented to measure the impact from the implementation of activities on landscape, without a solution which allows managing the landscape by itself. Taking into account all the aforementioned considerations the closest solution to ELC standards comes from mixture methods based on aesthetic attributes. But if theoretically this combination provides the optimal solution, in practice problems derived from the lack of systematization and objectivity, handling, universality or even from consideration of perception will have to be overcome.Therefore, the main objective of this paper is to develop a method of landscape assessment in accordance to standards from ELC. The method will be based on a mixture approach using aesthetic attributes measured through variables that guaranteed objectivity and systematization throughout the whole process. Having achieved the main objective, the following sub-objectives will also be reached: (1) to get a set of variables to quantify objectively and systematically aesthetic attributes, (2) to analyze population preferences in order to find a methodology to incorporate them into the management model and (3) to develop a method to explain and predict preferences for a specific type of landscape from the quantification of its attributes.

MATERIALS & METHODS

In order to achieve the aforementioned objectives, it is necessary to define a methodology based on the following steps: (1) select a particular type of landscape and to characterize its attributes, (2) develop a set of variables able to quantify those attributes in an objective, systematized and easy way, (3) measure those variables in the selected type of landscape, (4) collect population preferences for the selected landscape, and (5) develop an explanatory and predictive model for landscape preferences by variables related to aesthetic attributes. A region called La Moraña in the province of Ávila (Spain) was selected in order to define the scope of the model (Fig. 1 shows the location and the map of the region and several photographs used to develop the model) according to criteria of visual homogeneity and absence, at least a priori, of singularity. Land use which characterizes this landscape and guarantees visual homogeneity is cereal crops (Mata Olmo and Sanz Herraiz, 2003). It has been resorted to aesthetic attributes to characterize selected landscape due to its closeness to perception and its universality. Among the variety of existing attributes, those studied by Smardon *et al.* (1979) have been selected. But the methodologies to quantify those attributes have been only partially based on these authors´ works because do not always provide objective and systematizable tools able to quantify them. Thus, a set of variables, able to quantify every attribute in an easy, objective and systematized way, has been proposed trying to characterize the attributes in the broadest sense and assuming that its main function was to become explanatory variables inside a model of preferences. So they were referred to physical dimensions like length, area, angle, radius or luminosity. All variables included in the following tables 1 to 6 have been divided between generic characteristics and particularized ones. Variables that characterize the first analyzed attribute, lines, are shown in Table 1. Table 2 shows the variables aimed at quantifying the forms attribute. Smardon *et al.* (1979) categories based on geometry and complexity have been taken into account, although two intermediate classes in every category have been grouped into a single class in order to simplify its identification on photographs. In concrete "fairly geometric" and "intermediate" for geometry have

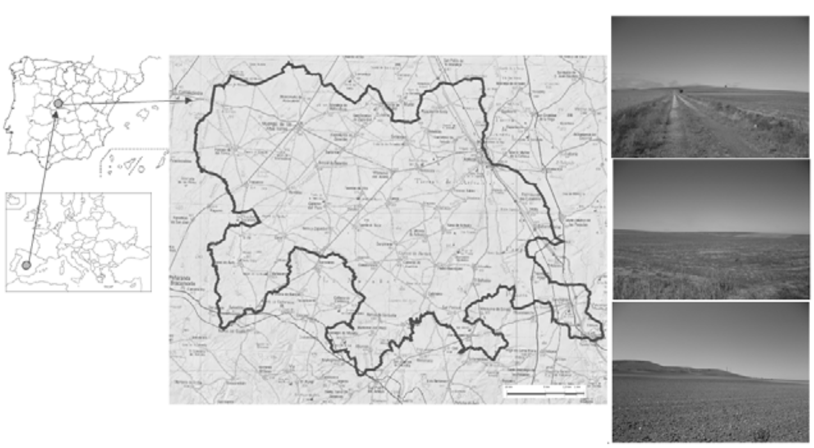

Fig. 1. The location and the map of the region and several photographs used to develop the model

Table 1. Variables used to characterize the lines attribute

Generic Variables	
Total number of lines (CTL), Mean length lines (LML), Standard deviation mean length (DTLL), Coefficient of variation (CVLL)	
Particularized Variables	
Straight lines: Total number of straight lines (LCR) Length Mean (LLR), Standard deviation (LDTLLR), Coefficient of variation (LCVLLR) Angle Mean (LAR), Standard deviation (LDTAR), Coefficient of variation (LCVAR)	Curved lines: Total number of curved lines (LCC) Length: Mean (LLC), Standard deviation (LDTLC), Coefficient of variation (LCVLC) Radius Mean (LRC), Standard deviation (LDTRC), Coefficient of variation (LCVRC)

Table 2. Variables used to quantify the forms attribute

Generic Variables	
Number of forms (CTF), Mean surface (SMF), Standard deviation mean surface (DTSMF), Coefficient of variation mean surface (CVSMF), Mean length axis form (LMEJEF), Standard deviation mean length axis form (DTLMEJEF), Coefficient of variation mean length axis form (CVLMEJEF), Mean angle axis form (AMEJEF), Standard deviation mean angle axis form (DTAMEJEF), Coefficient of variation mean angle axis form (CVAMEJEF)	
Particularized Variables	
Geometry	Geometric: Number of geometric forms (FCGG), Proportion (FPGG), Mean surface (FSGG), Standard deviation (FDTSGG), Coefficient of variation (FCVSGG). Intermediate: Number of intermediate forms (FCIG), Proportion (FPIG), Mean surface (FSIG), Standard deviation (FDTSIG), Coefficient of variation (FCVSIG). Amorphous: Number of amorphous forms (FCAG), Proportion (FPAG), Mean surface (FSAG), Standard deviation (FDTSAG), Coefficient of variation (FCVSAG).
Complexity	Simple: Number of simple forms (FCSC), Proportion (FPSC), Mean surface (FSSC), Standard deviation (FDTSSC), Coefficient of variation (FCVSSC) Intermediate: number of intermediate forms (FCIC), Proportion (FPIC), Mean surface (FSIC), Standard deviation (FDTSIC), Coefficient of variation (FCVSIC) Complex: Number of complex forms (FCCC), Proportion (FPCC), Mean surface (FSCC), Standard deviation (FDTSCC), Coefficient of variation (FCVSCC)

been collapsed to "intermediate" and "intermediate" and "fairly complex" for complexity have been collapsed to "intermediate".

The variables that quantify the texture attribute (Table 3) required additional specificity because Smardon *et al.* (1979) defined texture categories in a subjective way. So boundaries to limit every category had to be specified to guarantee the objectivity. Limits were adopted in the present work for grain surfaces (measuring attributes on a photograph of dimensions 0.1×0.075 m) as follows: fine texture, ($S_{grain}<1\times10^{-5}$ m^2), medium texture, (1×10^{-5} m^2 $\leq S_{grain}<1\times10^{-4}$ m^2) and gross texture ($S_{grain}\geq1\times10^{-4}$ m^2). The variables related to spatial composition (see Table 4) are focused on characteristics of the horizon line and on distribution of surfaces between sky and the rest of the photograph. The scale attribute as defined by Smardon *et al.* (1979) would create some problems if the contrast of any specific activity wanted to be implemented on the landscape is not desired to be analyzed. In the present work contrast criterion has been respected but referred to any element present in the scene which would contrast with any other attribute in the photograph. For these contrasting elements, surfaces and axis characteristics (where axis is determined by the widest dimension of the element) have been measured as previously mentioned in table 2 for forms attribute but avoiding its geometry or complexity classification (see Table 5).

The latest analyzed attribute was color. For its characterization, two different color measurement methods have been used: RGB and Lab (a complete

Table 3. Variables used to quantify the texture attribute

Generic Variables		
Number of grains (CTT), Mean surface (SMT), Standard deviation (DTSMT), Coefficient of variation (CVSMT)		
Particularized Variables		
Fine Grains: Number of fine grains (TCF), Proportion (TPF), Mean surface (TSF), Standard deviation (TDTSF), Coefficient of variation (TCVSF)	Medium grains: Number of medium grains (TCF), Proportion (TPF), Mean surface (TSF), Standard deviation (TDTSF), Coefficient of variation (TCVSF)	Gross grains: Number of gross grains (TCG), Proportion (TPG) Mean surface (TSG), Standard deviation (TDTSG), Coefficient of variation (TCVSG)

Table 4. Variables used to quantify the spatial composition attribute

Generic Variables	
Total number of lines in skyline (CTLCE), Mean length (LMLCE), Standard deviation mean length (DTLMCE), Coefficient of variation mean length (CVLMCE)	
particularized variables	
Straight lines: Number of straight lines (LCR)	Curved lines: Number of curved lines (LCC)
Length: Mean (LLR), Standard deviation (LDTLLR), Coefficient of variation (LCVLLR)	Length: Mean (LLC), Standard deviation (LDTLC), Coefficient of variation (LCVLC)
Angle: Mean (LAR), Standard deviation (LDTAR), Coefficient of variation (LCVAR)	Radius: Mean (LRC), Standard deviation (LDTRC), Coefficient of variation (LCVRC)
Photograph surfaces: Proportion of sky surface (SSK), Proportion of rest surface (STER)	

Table 5. Variables to quantify the scale attribute.

Elements: Total number of elements included in the scale attribute (CE), Mean surface (SME), Standard deviation mean surface (DTSME), Coefficient of variation mean surface (CVSME)	
Axis	Length: Mean (LEJEE), Standard deviation (DTLEJEE), Coefficient of variation (CVLEJEE) Angle: Mean (AME), Standard deviation (DTAME), Coefficient of variation (CVAME)

description of these color measurement modes can be seen in Fairchild, 2005). Variables related to each of the methods are included in Table 6.

Each variable set forth in Table 6 has been measured twice, once in the complete image and another one in the photograph where sky was cut off. This necessity was triggered by the distortion exerted by the presence of the sky on color histograms, not only on blue spectrum but on all of them (differences between both histograms can be seen in Fig. 2). For a better characterization of color contrast, absolute value of differences between color measurement, as well as standard deviation and coefficient of variation, were calculated. Every variable displayed in Tables 1 to 6 was modeled on photographs generating schemes for every attribute and photograph to measure them as shown in fig. 2. Lines, forms, texture, scale and spatial composition schemes were drawn using AutoCAD (version 2000) and afterwards all variables were measured. Color histograms were extracted using Irfanview (version 4.33) and ImageJ (version 1.48).

Once variables were defined, surveys were carried out to collect population preferences about analyzed landscape. As it would be impossible to represent all ranges in attributes and variables, and all the possible combinations for every variable displayed in Tables 1 to 6, from an initial intake of 1,518 photographs, surveys were limited to 100 photographs selected to reach the optimum between the best characterization of the attributes and the practicality of surveys. Photographs were exposed on random order to avoid the influence of previously shown photographs on valuations. All of them were valuated using a five point Likert-type scale between *I do not like it at all* (value 1) and *I like it a lot* (value 5). There exist innate and acquired factors that could influence people on landscape perception and valuation (Van den Berg *et al.*, 1998). So if acquired factors explain differences on landscapes preferences, then they have to be taken into account for sample selection. Among the acquired factors, place of residence was chosen to select the sample, assuming its relevance as Van den Berg and Koole (2006) evidenced. Thus, a stratified sampling method was

Table 6. Variables used to quantify the color attribute in RGB and Lab methods

Generic variables	
	RGB: Mean (MRGB), Standard deviation (DTRGB), Coefficient of variation (CVRGB).
	RGB-Green: Absolute value of the mean difference between RGB and green (RGBGREEN).
	RGB-Blue: Absolute value of the mean difference between RGB and blue (RGBBLUE).
	RGB-Red: Absolute value of the mean difference between RGB and red (RGBRED).
	Lab: Mixed mean (MMIX), Mixed standard deviation (DTMMIX), Mixed coefficient of variation (CVMMIX)
Particularized Variables	
RGB	Red: Mean (CMR), Standard deviation (CDTR), Coefficient of variation (CCVR).
	Green: Mean (CMV), Standard deviation (CDTV), Coefficient of variation (CCVV).
	Blue: Mean (CMA), Standard deviation (CDTA), Coefficient of variation (CCVA).
	Red-Green: Absolute value of the mean difference between red and green gamma (RV).
	Red-Blue: Absolute value of the mean difference between red and blue gamma (RA).
	Blue-Green: Absolute value of the mean difference between blue and green gamma (VA).
Lab	L: Mean (CML), Standard deviation (CDTL), Coefficient of variation (CCVL)
	a: Mean (CMa), Standard deviation (CDTa), Coefficient of variation (CCVa)
	b: Mean (CMb), Standard deviation (CDTb), Coefficient of variation (CCVb)
	a-b: Absolute value of the mean difference between a and b values (Ca-b)

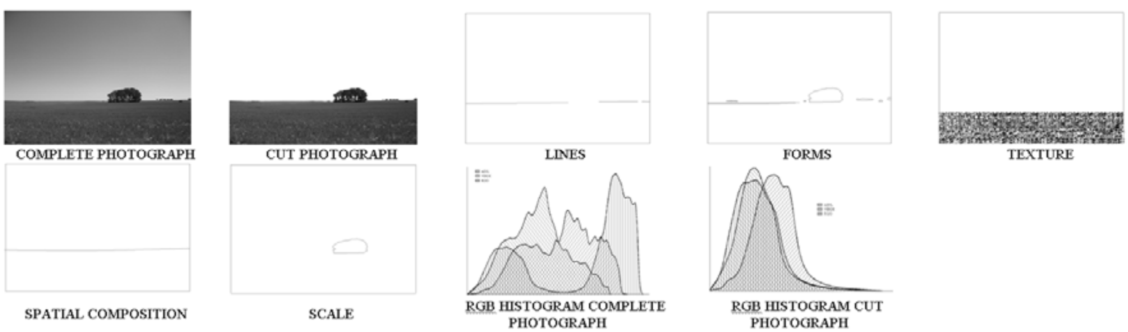

Fig. 2. Lines, forms, texture, scale and spatial composition schemes

used defining three strata in accordance to residence criterion: strongest relationship with the landscape (inhabitants of the region), weakest relationship with the landscape (large cities far from to the type of landscape), and a third intermediate stratum (medium-sized cities surrounded by this type of landscape). The sample is a convenience sample of 125 people, 52 belonging to strongest relationship stratum, 42 intermediate and 31 to weakest stratum. But in addition to the residence criterion, and looking for an unbiased sample, individuals were selected balancing other acquired factors such as age, studies, birthplaces or the type of relationship with landscape. Table 7 shows the composition of the sample according to these factors. The pursued method has to be able to explain population preferences for landscape (dependent variable) through variables that allowed quantifying aesthetic attributes (independent variables). But before building the model, it was necessary to group independent variables to avoid multi collinearity (caused by color measurement in two different modes, for example) or problems derived from the presence of linear combinations like, for example, variables related to global features (total number of lines) and particularized ones (number of straight lines and number of curved lines). These circumstances led to group variables into eight classes outlined in table 8. Each one of those classes includes the set of variables from tables 1 to 6 that meet specified requirements. For example, group 1 in table 8 is formed by the set of all generic variables referred to in tables 1 to 5 and Lab generic variables in table 6 measured in the complete photograph, while group 7 is formed by the set of all particularized variables referred in tables 1 to 5 and RGB particularized variables in table 6 measured in the sky cut photographs. Statistical models that establish the relation between dependent and independent variables in landscape related bibliography usually rely on linear relationships (Arriaza *et al*., 2004; Bishop, 1996; Cañas *et al*., 2009; Deng *et al*., 2013; Hofmann *et al*., 2012; Ramírez *et al*., 2011), while there are fewer applications of

Table 7. Composition of the sample according to social and cultural characteristics

Criteria	Group	Frequency
	<25 years	46 (36.8%)
Age	25-45 years	36 (28.8%)
	>45 years	43 (34.4%)
	Closest (Towns or villages around landscape)	39 (31.2%)
Birth place	Intermediate (Main cities in province around landscape)	44 (35.2%)
	Farthest (Big cities and capitals far from landscape)	42 (33.6%)
Educational level	Undergraduate	62 (49.6%)
	Graduate or higher	63 (50.4%)
	Maximum (living or working)	40 (32.0%)
Type of relation with landscape	Medium (holidays or second residence)	37 (29.6%)
	Minimum (no relation)	48 (38.4%)

Table 8. Groups of variables according to its type and color measurement mode

Complete Photograph	Cut Photograph
1. Generic variables - Lab	5. Generic variables -Lab
2. Generic variables - RGB	6. Generic variables - RGB
3. Particularized variables - Lab	7. Particularized variables - RGB
4. Particularized variables - RGB	8. Particularized variables - Lab

nonlinear models (Franco *et al.*, 2003). In this work both linear and nonlinear regressions have been used, where the dependent variable is the average of values expressed by the 125 respondents and independent ones are those exposed in tables 1 to 6 for every photograph. Eight different process of linear regression analysis have been run for every group of independent variables referred in table 8. Generalized least squares technique has been employed to determinate regression coefficients because of the risks from correlations between independent variables and a backward elimination method entering all variables and removing non-significant ones sequentially has been preferred to identify the optimal set of variables. Nonlinear models, using a logarithmic, inverse, quadratic, cubic, powder, s-curve, growth, exponential, compound logistic expression, and combinations among them, have also been tried using Gauss-Newton method.The optimal model has been selected according to adjusted coefficient of determination while explanatory power has been referred to coefficient of determination (Achen, 1982). Typified coefficients have been employed to analyze weights of every variable on predicted value. F- and t-tests, considering a significance level of 5%, have been used to contrast the goodness of fit. Both tests can be considered proper even though normality distribution of residuals cannot be strictly proved (Gujarati, 1995).

RESULTS & DISCUSSION

Statistical tests for regression functions referred above have been run for every group of variables included in table 8, deducing the concrete regression formula and coefficients of determination. Table 9 shows results for those operations for optimal (according to adjusted coefficient of determination) and best explanatory models (according to coefficient of determination) inside every group of variables.

Explanatory power for nonlinear models is lower in all cases, being the highest coefficient of determination 0.345, thanks to a compound model using mean value of the brightness (CML) in Lab mode. So, nonlinear models were not included in table 9. Also models which include particularized variables provide a greater explanatory power than those built upon generic ones. Indeed, the model with the greatest explanatory power (numbered 15 in table 9, whose coefficient of determination is equal to 0.827) include 60 particularized variables measured on photographs with the sky cut and using RGB mode. However, according to adjusted coefficient of determination, optimal model is 16, including only 41 variables of the 60 included in model 15. Adjusted coefficient of determination for this model amounts to 0.698, while the absolute one amounts to 0.823. The goodness of the explanatory power for model 16 is further guaranteed by F-Test ($F = 6.57$, p-value = 0.000). But even if adjusted coefficient of determination must be used to select the optimal model, explanatory power comes from the absolute one. It can therefore be concluded that model number 16 is able to explain 82.3% of preferences variance for analyzed photographs, implying complementarily that 17.7% of preferences in variance cannot be explained from aesthetic attributes and used variables.The first

Table 9. Coefficients of determination for the best models inside every group of variables

Model	Variables Cluster	R^2	$R^2_{adjusted}$	Model	Variables Cluster	R^2	$R^2_{adjusted}$
1	Complete photograph,	0.486	0.312	9	Complete photograph,	0.811	0.509
2	generic variables, Lab	0.473	0.364	10	particularized variables, Lab	0.794	0.629
3	Complete photograph,	0.609	0.446	11	Complete photograph,	0.804	0.489
4	generic variables, RGB	0.601	0.506	12	particularized variables, RGB	0.791	0.631
5	Cut photograph, generic	0.554	0.395	13	Cut photograph, particularized	0.810	0.517
6	variables, Lab	0.542	0.447	14	variables, Lab	0.792	0.650
7	Cut photograph, generic	0.647	0.501	15	Cut photograph, particularized	0.827	0.565
8	variables, RGB	0.634	0.541	16	variables, RGB	0.823	0.698

Table 10. Regression coefficients and significance (t-Test) for variables included in model 16

Variable	B_i	B_i Typified	Sign (Test t)	Variable	B_i	B_i Typified	Sign (Test t)
(Constant)	-5.293		0.019	TSM	0.641	0.192	0.019
LCR	-0.011	-0.296	0.014	TCVSG	0.102	0.187	0.042
LAR	0.003	0.132	0.121	CECR	0.051	0.151	0.268
LCC	0.014	0.194	0.118	CECVLR	0.522	0.355	0.009
LRC	$-3.9\cdot10^{-5}$	-0.084	0.224	CEAR	-0.026	-0.273	0.003
FCGG	-0.091	-0.902	0.002	CECVAR	-0.442	-0.285	0.020
FCVSGG	0.519	0.436	0.011	CECC	0.055	0.320	0.002
FCIG	0.031	0.291	0.047	CELC	0.003	0.152	0.101
FSIG	0.004	0.732	0.002	CERC	$-2.6\cdot10^{-5}$	-0.177	0.032
FCVSIG	0.186	0.173	0.124	CECVR	-0.201	-0.207	0.032
FSAG	0.003	0.780	0.006	ES	$-2\cdot10^{-4}$	-0.314	0.024
FCSC	0.099	1.054	0.000	EL	0.003	0.196	0.148
FSSC	0.002	0.094	0.234	ECVL	0.608	0.314	0.058
FCVSSC	-0.529	-0.481	0.000	EA	0.004	0.242	0.004
FSIC	-0.003	-0.687	0.011	ECVA	0.203	0.160	0.246
FCVSIC	-0.346	-0.382	0.000	CMR	-0.170	-6.919	0.000
FCCC	-0.011	-0.121	0.154	CMV	0.421	14.571	0.000
FSCC	-0.003	-0.647	0.009	CCVV	62.544	11.802	0.000
TCF	$4.76\cdot10^{-5}$	0.458	0.000	CMA	-0.229	-9.408	0.000
TCVSF	-0.312	-0.230	0.009	CCVA	8.151	1.879	0.041
TCM	$-9.4\cdot10^{-5}$	-0.197	0.031	RA	-64.901	-14.620	0.000

conclusion deduced from Table 10, where coefficients of regression and t-Test for every variable included in the selected model (model 16) are shown, is about the relevance of those coefficients related to the color attribute. The less relevant typified coefficient related to color (coefficient of variation in blue range, CCVA), which amounts to 1.879, is 78.27% higher than the previous one in order of relevance (number of simple forms, FCSC), which amounts to 1.054. Fig. 3a shows the weight of each attribute inside the model (sum of typified coefficients of regression for each attribute) where the relevance of the color attributes can be clearly seen. Moreover, fig. 3b points out the importance of every variable inside the color attribute (proportion between every typified coefficient for every variable related to color and the sum of all typified coefficients for color variables). Attending to the color attribute (fig. 3b and Table 10), it can be concluded that higher values in typified coefficients come from mean green (CMV) with positive sign and from difference between red and blue (RA) with negative sign. The only two variables related to red color included in the model (CMR and RA) exert a negative influence on predicted value, specially the last one with a typified coefficient of -14.620. The variable referred to the mean brightness of blue gamma (CMA) is also perceived in a highly negative sense by population with a typified coefficient of -9.408. Regression coefficients for the most relevant variables (all related to the color attribute) are statistically significant according to the t-Test (Table 10). This fact also proves the validity of the model and the importance of the color attribute on predicted preferences values. It has been proved that the exposed method is statistically correct and agrees with ELC as it considers population preferences in a similar way to other works which attempt to explain preferences (Arriaza *et al.*, 2004; Cañas *et al.*, 2009; Ramírez *et al.*, 2011) or scenic beauty (Franco *et al.*, 2003; Luckmann *et al.*, 2013; Schirpke *et al.*, 2013). It allows overcoming discussion between experts based models and preferences models referred by Shirpke *et al.* (2013) because the presented method can be applied by experts but results emanate from population preferences. The deduced method also agrees with ELC by allowing any landscape the self-management independently of expected impacts from activities susceptible to be implemented, improving solutions provided for other methods such as Smardon *et al.* (1979). Nevertheless, it does not preclude using the deduced methodology to predict impacts arising from activities just using photomontages and calculating values through the inferred method in situations before and after the implementation of the activity. The methodology agrees with ELC due to its consideration of the territorialized character of the landscape. The developed method avoids its universal application and defines its scope only for a specific type of landscape characterized for the dominance of extensive cereal crops. The defined strategy for attributes characterization allows its objective and systematized measurement, not based on subjective measurements scales, overcoming problems often ascribed to those attributes as recognized by Frank *et al.* (2013). In addition to its objectivity, both the attributes and variables have the advantage of allowing greater universality and simplicity in the practical measurement of landscape value. There are several models that link landscape preferences with its attributes (Arriaza *et al.*, 2004; Cañas *et al.*, 2009; Schirpke *et al.*, 2013), but they usually resort to physical attributes which are neither easy to measure nor applicable for landscapes different from those which were developed for, while variables deduced in this paper are susceptible to be used in any landscape, although the concrete expression to deduce their value has to be obtained through preferences specifically expressed for every landscape. Existing works related to the psychology of perception, aforementioned in this paper, show that the perception and evaluation process presents complex mechanisms that deviate from linearity. However, those works also show that initial stages of this process, when aesthetic attributes are perceived, turn out to be simpler so that the individual and independent perception of aesthetic attributes can be accepted. Therefore perception and interpretation of those attributes would be objective and common for all people, as it is not affected by mental subjective procedures. Those theories would endorse linear models, as the developed in the present paper, to characterize earlier stages of human perceptual process. They also allow stating that the explanatory power of the deduced model is clearly linked to the common portion of population preferences in perception and interpretation of lines, forms, texture, scale, spatial composition and color. Finally, previous arguments also allow asserting that the deduced method agrees with ELC due to the inclusion of perception.

Focusing now on the argument of concrete results and structure of the deduced method, the set of variables related to aesthetic attributes have allowed achieving an explanatory power of 82.3% of the variance preferences for the selected type of landscape. Other authors have obtained results close to this figure. Ramírez *et al.* (2011) explained 96.24% using a different kind of attributes in the area of rural roads, Franco *et al.* (2003) got 99.1% relative to the effect of certain agroforestry operations, Arriaza *et al.* (2004) reached 50% for rural landscapes while Schirpke *et al.* (2013) reached 72% for alpine scenery. If it is assumed that the percentage of variance explained by the model represents the common part of the population preferences, this level of agreement among individuals with different social and cultural characteristics could be related to the influence of innate factors, in the same way as conclusions drawn by Howley (2011), based on preferences for landscapes where water is present, or by Falk and Balling (2010) for savanna landscapes. At this point, the greatest importance of innate factors obtained in this work (up to 82.3% of preferences) would be consistent with findings drawn by Adevi and Grahn (2012), Cañas *et al.* (2009), Kearney *et al.* (2008) or Ode *et al.* (2009) which concluded that differences among sociological groups are not too relevant. As the deduced methodology is able to explain 82.3% of the variance in preferences, attributable to innate factors, the remaining 17.7% would be caused, according to Franco *et al.* (2003), by the effect of social and cultural acquired factors. Van den Berg and Koole (2006) found that the influence of those factors would explain 16% of preference for landscapes with different degrees of human intervention in a similar way to findings from Howley *et al.* (2012) or Svobodova *et al.* (2012). The greatest relevance of the color attribute observed in this work is consistent with conclusions drawn by González (2000) related to landscape perception, which proved the greater relevance of this attribute. Inside the color attribute, the variable that exerts the greatest positive influence is green brightness. There is a seasonal component in the analyzed landscape which would determine perceived color, and green gamma is typical of spring and autumn but in order to minimize this seasonal effect, the method has been developed using different type of crops and color composition. It is true that for the same place the method could lead to different values depending on the season, but it is also true that perception, and therefore landscape, would not be the same in those different moments. Moreover, the relevance of green brightness from vegetation has also been found by other authors such as Hörnstern and Fredman (2000), Kaltenborn and Bjerke (2002), and with other studies that demonstrated higher preferences for plant elements, such as Arriaza *et al*. (2004). In contrast to green brightness, red gamma exerts the worst influence. This lower preference linked to red may be related to the presence of tilled plots in several photographs, results in line with Lindemann-Matthies *et al*. (2010).

CONCLUSION

A method to assess agricultural landscapes characterized by the presence of cereal crops has been deduced. It has been inferred from population preferences and a set of variables capable of quantifying aesthetic attributes in a simple, objective and systematized way. The method agrees with ELC because it considers perception and population preferences and respects territorialized character of landscape. It has been proved that there is a set of variables that can be objectively measured in photographs allowing an objective and systematic quantification of aesthetic attributes. Those variables are referred to lines, forms, color, texture, spatial composition and scale and related to physical dimensions such as length, area, radius, angle and brightness. Using those variables as the independent ones, a predictive and explicative method of preferences for agricultural landscapes expressed by the population has been built. The final model has been deduced by testing linear and nonlinear regression models and is able to explain 82.3% of variance in preferences. Major influence on preferences for this type of landscape (82.3 %) comes from innate factors common for all population, to the extent that it can be accepted that people perceive and interpret aesthetic attributes in the same way. Conversely, 17.7% of preferences are due to acquired factors supposed different for everyone.

The deduced model has a linear structure and is built upon 41 variables measured on photographs with the sky cut and with color characterized by RGB mode. All attributes are included in the model but the most relevant one in terms of explanatory power, far above the others, is color. The most relevant variables inside the model to explain preferences are green brightness with a positive sign and difference between blue and red brightness gamma with a negative sign.

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REFERENCES

Achen, C. H. (1982). Interpreting and using regression, Vol. 29. London: Sage Publications.

Adevi, A. A. and Grahn, P. (2012). Preferences for Landscapes: A Matter of Cultural Determinants or Innate Reflexes that Point to Our Evolutionary Background? Landscape Research, **37 (1)**, 27-49.

Arriaza, M., Cañas-Ortega, J. F., Cañas-Madueno, J. A. and Ruiz-Aviles, P. (2004). Assessing the visual quality of rural landscapes. Landscape and Urban Planning, **69 (1)**, 115-125.

Berleant, A. (2010). Reconsidering Scenic Beauty. Environmental Values, **19 (3)**, 335-350.

Bishop, I. D. (1996). Comparing regression and neural net based approaches to modelling of scenic beauty. Landscape and Urban Planning, **34 (2)**, 125-134.

Cañas, I., Ayuga, E. and Ayuga, F. (2009). A contribution to the assessment of scenic quality of landscapes based on preferences expressed by the public. Land Use Policy, **26 (4)**, 1173-1181.

Daniel, T. C. (2001). Whither scenic beauty? Visual landscape quality assessment in the 21st century. Landscape and Urban Planning, **25**, 267-281.

Daniel T. C. and Boster, R. S. (1976). Measuring landscape esthetics: the scenic beauty estimation method (Research Paper RM–167). (Washington: USDA Forest Service). Retrieved February 13, 2013, from http://www.fs.fed.us/rm/value/docs/scenic_beauty_estimation.pdf.

Deng, S. Q., Yan, J. F., Guan, Q. W. and Katoh, M. (2013). Short-term effects of thinning intensity on scenic beauty values of different stands. Journal of Forest Research, **18 (3)**, 209-219.

Edwards, D., Jay, M., Jensen, F. S., Lucas, B., Marzano, M., Montagne, C., Peace, A. and Weiss, G. (2012). Public preferences for structural attributes of forests: Towards a pan-European perspective. Forest Policy and Economics, **19**, 12-19.

Fairchild, M. D. (2005). Color Appearance Models. Chichester: Wiley-IS&T.

Falk, J. H. and Balling, J. D. (2010). Evolutionary Influence on Human Landscape Preference. Environment and Behavior, **42 (4)**, 479-493.

Franco, D., Franco, D., Mannino, I. and Zanetto, G. (2003). The impact of agroforestry networks on scenic beauty estimation - The role of a landscape ecological network on a socio-cultural process. Landscape and Urban Planning, **62 (3)**, 119-138.

Frank, S., Furst, C., Koschke, L., Witt, A. and Makeschin, F. (2013). Assessment of landscape aesthetics-Validation of a landscape metrics-based assessment by visual estimation of the scenic beauty. Ecological Indicators, **32**, 222-231.

García, L., Hernández, J. and Ayuga, F. (2003). Analysis of the exterior colour of agroindustrial buildings: a computer aided approach to landscape integration. Journal of Environmental Management, **69 (1)**, 93-104.

García, L., Hernández, J. and Ayuga, F. (2006). Analysis of the materials and exterior texture of agro-industrial buildings:

a photo-analytical approach to landscape integration. Landscape and Urban Planning, **74 (2)**, 110-124.

García-Moruno L., Montero-Parejo M. J., Hernández-Blanco J. and López-Casares, S. (2010). Analysis of lines and forms in buildings to rural landscape integration. Spanish Journal of Agricultural Research, **8 (3)**, 833-847.

Gobster, P. H. and Chenoweth, R. E. (1989). The dimensions of aesthetic preference - a quantitative-analysis. Journal of Environmental Management, **29 (1)**, 47-72.

González, R. (2000). La fotografía como elemento para el análisis y la simulación del paisaje forestal. Unpublished Ph.D dissertation. Polytechnic University of Madrid. Madrid.

Gujarati, D. N. (1995). Basic Econometrics. New York: McGraw-Hill.

Hofmann, M., Westermann, J. R., Kowarik, I. and Van der Meer, E. (2012). Perceptions of parks and urban derelict land by landscape planners and residents. Urban Forestry and Urban Greening, **11 (3)**, 303-312.

Hörnstern, L. and Fredman, P. (2000). On the distance to recreational forests in Sweden. Landscape and urban planning, **51 (1)**, 1-10.

Howley, P. (2011). Landscape aesthetics: Assessing the general public preferences towards rural landscapes. Ecological Economics, **72**, 161-169.

Howley, P., Donoghue, C. O. and Hynes, S. (2012). Exploring public preferences for traditional farming landscapes. Landscape and urban planning, **104 (1)**, 66-74.

Kaltenborn, B. and Bjerke, T. (2002). Visualization on forest landscape preference research: a finish perspective. Landscape and urban planning, **59 (1)**, 1-11.

Kearney, A. R., Bradley, G. A., Petrich, C. H., Kaplan, R., Kaplan, S. and Simpson-Colebank, D. (2008). Public perception as support for scenic quality regulation in a nationally treasured landscape. Landscape and Urban Planning, **87 (2)**, 117–128.

Lewis, K. J. S., Borst, G. and Kosslyn, S. M. (2011). Integrating visual mental images and visual percepts: new evidence for depictive representations. Psychological Research-Psychologische Forschung, **75 (4)**, 259-271.

Lindemann-Matthies, P., Briegel, R., Schupbach, B. and Junge, X. (2010). Aesthetic preference for a Swiss alpine landscape: The impact of different agricultural land-use with different biodiversity. Landscape and Urban Planning, **98 (2)**, 99-109.

Luckmann, K., Lagemann, V. and Menzel, S. (2013). Landscape Assessment and Evaluation of Young People: Comparing Nature-Orientated Habitat and Engineered Habitat Preferences. Environmental and behavior, **41 (1)**, 86-112.

Mata Olmo, R. and Sanz Herraiz, C. (Dirs.) (2003) Atlas de los paisajes de España. Madrid: Ministerio de Medio Ambiente.

Moutoussis, K. and Zeki, S. (1997). A direct demonstration of perceptual asynchrony in vision. Proceedings of the Royal Society B-Biological Sciences, **264**, 393-399.

Moutoussis, K. and Zeki, S. (1997b). Functional segregation and temporal hierarchy of the visual perceptive systems. Proceedings of the Royal Society B-Biological Sciences, **264**, 1407-1414.

Ode, Å., Fry, G., Tveit, M. S., Messager, P. and Miller, D. (2009). Indicators of perceived naturalness as drivers of landscape preference. Journal of Environmental Management, **90 (1)**, 375–383.

Ramírez. A., Ayuga, E., Gallego, E., Fuentes, J. M. and García, A. I. (2011). A simplified model to assess landscape quality from rural roads in Spain. Agriculture Ecosystems & Environment, **142 (3-4)**, 205-212.

Real, E., Arce, C. and Sabucedo, J. (2000). Classification of landscapes using quantitative and categorical data, and prediction of their scenic beauty in North-Western Spain. Journal of Environmental Psychology, **20 (4)**, 355-373.

Schirpke, U., Tasser, E. and Tappeiner, U. (2013). Predicting scenic beauty of mountain regions. Landscape and Urban Planning, **111**, 1-12.

Sevenant, M. and Antrop, M. (2010). The use of latent classes to identify individual differences in the importance of landscape dimensions for aesthetic preference. Land Use Policy, **27 (3)**, 827-842.

Smardon. R. C., Appleyard, D., Sheppard, S. R. J. and Newman, S. (1979). Prototype Visual Impact Assessment Manual. New York: Syracusa State University.

Svobodova, K., Sklenicka, P. and Molnarova, K. (2012). Visual preferences for physical attributes of mining and post-mining landscapes with respect to the sociodemographic characteristics of respondents. Ecological engineering, **43**, 34-44.

Van den Berg, A. E., Vleka, A. J. and Coeterier, J. F. (1998). Group differences in the aesthetic evaluation of nature development plans. A multilevel approach. Journal of Environmental Psychology, **18 (2)**, 141–157.

Van den Berg A. E. and Koole, S. L. (2006). New wilderness in the Netherlands: An investigation of visual preferences for nature development landscapes. Landscape and Urban Planning, **78 (4)**, 362-372.

Wherrett, J. R. (2000). Creating landscape preference models using the Internet as a medium for surveys. Landscape Research, **25 (1)**, 79-96.

Zhao, J. W., Wang, R. H., Cai, Y. L. and Luo, P. J. (2013). Effects of Visual Indicators on Landscape Preferences. Journal of Urban Planning and Development-ASCE, **139 (1)**, 70-78.