Valuing the view: Public preferences for aesthetic qualities of agricultural landscapes across Europe

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Acknowledgements: This work was funded from the LIFT (Low Income Farming and Territories) European Union's Horizon 2020 research and innovation programme under Grant Agreement No 770747.

1. Introduction

Agricultural landscapes are multifunctional social-ecological systems that deliver a wide range of ecosystem services to society. Conceptual frameworks such as the Common International Classification of Ecosystem Services (CICES) distinguish between three categories of ecosystem services, namely provisioning services (e.g., food and fiber production), regulating and maintaining services (e.g., soil formation), and cultural services including non-material benefits such as recreation and landscape aesthetics (CICES, 2018). While extensive research has focused the biophysical benefits of environmentally friendly farming practices – such as improved biodiversity, soil health, and carbon sequestration – the societal co-benefits of these transitions remain less systematically understood. In particular, there is comparatively limited empirical evidence on how citizens perceive and value the aesthetic consequences of ecological farming practices, and whether such preferences are shared across regions and social groups.

Among cultural ecosystem services, landscape aesthetics represent one of the most immediate and tangible ways in which agricultural management affects the general public. Visual landscape quality mediates everyday interactions between people and agricultural land and has been shown to influence psychological well-being and foster positive public attitudes towards land-use policies (Assandri et al., 2018; Csurgó and Smith, 2021; Daniel et al., 2012). Reflecting this importance, landscape aesthetics are explicitly recognized within ecosystem service frameworks and are central to the European Landscape Convention, which defines landscapes as "an area, as perceived by people" and calls for the integration of public perception into landscape policy, planning, and management (Council of Europe Landscape Convention, 2000). In parallel, recent reforms of the Common Agricultural Policy (CAP) increasingly emphasize the delivery of public goods, including cultural ecosystem services, through agri-environmental and climate measures. Understanding how citizens perceive and value the aesthetic consequences of more environmentally friendly farming practices is therefore directly relevant to European agricultural policy design and legitimacy.

Agricultural landscapes are shaped by a complex interplay between ecological processes, physical geography, and human decision-making. Land-use choices driven by economic performance, topographical constraints, and policy incentives determine the spatial distribution of natural elements such as hedgerows and grasslands, as well as built infrastructure including farm buildings, machinery, and renewable energy installations (Plieninger et al., 2013). As farming systems incorporate more environmentally friendly practices, they not only enhance ecosystem functioning but also alter the visual character of rural landscapes (Fry et al., 2009). For example, diversified cropping systems and reduced mechanization can create visually and ecologically richer landscapes (Lindemann-Matthies et al., 2010). Similarly, the adoption of renewable infrastructure, such as small-scale wind and solar voltaic installations on farms, alters rural aesthetics while contributing to sustainability and green energy goals (Chel and Kaushik, 2011; Nadaï and van der Horst, 2010).

Public responses to these visual changes are not uniform. While many studies show that visually appealing landscapes foster positive attitudes towards land-use policies (Assandri et al., 2018; Csurgó and Smith, 2021; Daniel et al., 2012), ecological transitions in agriculture can also provoke ambivalent reactions. Practices such as increases landscape diversity or the introduction of renewable energy infrastructure may be interpreted as signs of stewardship and environmental responsibility by some, they may also be perceived as distributive of traditional rural aesthetics and identity (Hevia-Koch and Ladenburg, 2019; Paarlberg, 2023; Tribot et al., 2018). Although a substantial and growing body of literature examines agricultural landscape aesthetics, fewer studies explicitly assess how visual changes associated with environmentally friendly farming practices are valued as co-benefits alongside implicit environmental outcomes, particularly in a cross-geographic comparative approach.

This study aims to fill this gap in the literature by assessing how citizens value the aesthetic dimension of agricultural landscapes shared by varying levels of environmentally friendly management, and by examining how these preferences differ across socio-demographic groups. Using a Discrete Choice Experiment (DCE), we estimate preferences and willingness to pay (WTP) for landscape characteristics that reflect transitions from intensive conventional practices to more diversified and extensive farming approaches. As public goods, landscapes lack market prices, making stated preference methods particularly suitable for eliciting the trade-offs individuals are willing to make between different landscape attributes and associated costs (Lancsar et al., 2017; Train, 2009). Building on recent applications of image-based DCEs in landscape research (summarized in Appendix A, Table A1), this study employs digitally manipulated images to ensure consistent visual representation of agricultural management practices across study regions and to support respondents in evaluating complex aesthetic trade-offs.

The analysis is conducted across three European regions, namely Flanders (Belgium), Hungary, and the United Kingdom (UK), to examine whether aesthetic preferences for ecologically managed agricultural landscapes are primarily shaped by local socio-cultural and policy contexts or whether more generalizable patterns emerge. The regions differ in agricultural structure, rural planning traditions, and policy frameworks, yet share comparable mixed-livestock landscapes, allowing for meaningful cross-country comparison. This design allows us to test the relevance of landscape aesthetics as a cultural ecosystem service within the context of EU-wide policy instruments such as the CAP, while also identifying potential sources of preference heterogeneity. Specifically, we address two research questions: (i) how are aesthetic components of agricultural landscapes associated with more environmentally friendly management practices valued by the public, and (ii) how do preferences vary across different socio-demographic groups? By explicitly linking landscape aesthetics to ecological management and policy relevant contexts, this study contributes to a more comprehensive understanding of the societal co-benefits of sustainable agricultural transitions.

2. Literature overview

Aesthetic preferences for agricultural landscapes are influenced by a range of both intrinsic landscape characteristics and observer-related factors, including knowledge, experience, and values (Qi et al., 2022). Landscape assessment approaches are commonly grouped into three categories: objective (expert-based or indicator-driven), subjective (perception- or preference-based), and mixed approaches that integrate physical landscape attributes with public preferences (Kang and Liu, 2022). As the objective of this work is to assess citizens' preferences of agricultural landscapes explicitly linked to the adoption of more environmentally friendly farming practices, we adopt a subjective, preference-based approach. We view this as a first step in transitioning towards an integrative assessment in which landscape-level management interventions can ultimately be evaluated across multiple ecosystem service dimensions.

One of the most consistent findings in the literature is that landscape diversity strongly influences public preferences. Homogeneous, monotonic landscapes are generally perceived as less attractive compared to more varied, mosaic-like environments. This visual diversity may arise though the integration of natural landscape elements into agricultural land, mixed land uses such as arable fields and pasture, or variations in crop types within a rotation. Non-crop features, such as trees, hedgerows, or other signs of land stewardship, are frequently associated with higher aesthetic value and interpreted as indicators of environmental care (Rust et al., 2021; Stokstad et al., 2020).

Empirical studies reinforce these findings. For example, Stokstad et al. (2020) observed that landscapes with additional non-crop elements are preferred because they signal active stewardship, while Rust et al. (2021) find that diversified land use, including the presence of grazing animals, enhances visual appeal. However, preferences are not uniform. In Mediterranean regions, Bidegain et al. (2020) found support for both traditional monoculture agricultural landscapes and more heterogeneous, mosaic-type landscapes, suggesting that cultural familiarity, historic land-use patterns, and regional identity also play a role.

Beyond vegetation and land use, non-green infrastructure plays an important role in shaping perceptions of agricultural landscapes. Elements such as renewable energy installations like wind turbines and solar panels, farm buildings, and machinery, can either enhance or detract from landscape appeal depending on their scale, visibility, and perceived function. While these features can signal sustainability of productive land use, they may also be perceived as intrusive when poorly integrated. As a result, preferences for infrastructure-related elements are often non-linear, with moderate, well-sited interventions being more acceptable than dense or visually dominant ones (Butler and Wärnbäck, 2019; Hevia-Koch and Ladenburg, 2019; Jikiun et al., 2023).

Importantly, aesthetic preferences are not homogeneous across populations (Tatum et al., 2017). A growing body of literature shows that socio-demographic characteristics, environmental attitudes, education, and lived experience with rural landscapes systematically influence how landscapes are perceived and valued. Some individuals prioritize purely visual characteristics, while others focus on ecological or functional dimensions of landscapes, such as their capacity to deliver ecosystem services. For instance, Arnberger and Eder (2011) and Howley (2011) show that ecological awareness shape landscape preferences Wilhelm et al. (2020) find that landscape features associated with ecosystem services, especially those linked to clean water provision, are often valued more highly than purely visual attributes. These findings suggest that aesthetic evaluations are shaped not only by what is seen, but also by what is known and experienced, implying that mean preference estimates may mask meaningful heterogeneity (Kang and Liu, 2022).

Two main theoretical perspectives help explain these patterns. The first adopts an evolutionary and affective lens, proposing that people are drawn to landscapes that appear safe, orderly, and conducive to human well-being. This perspective suggests that well-managed landscapes, i.e., those showing clear signs of human care and stewardship, are preferred over wild or unmanaged environments (Kang and Liu, 2022; Tribot et al., 2018). Within this framework, features such as agricultural buildings, visible machinery, and maintained fields are interpreted as contributing positively to landscape value because they signal food provision and responsible land management. Aesthetic preferences, from this view, are considered relatively stable and universal (Swaffield and McWilliam, 2013).

In contrast, a second perspective sees aesthetic values as socially constructed and dynamic. Here, preferences are shaped by cultural context, personal experience, and environmental awareness, and may evolve over time and with exposure to new information (Hill and Daniel, 2008; Swaffield and McWilliam, 2013; Tribot et al., 2018). From this standpoint, individuals with greater environmental concerns or stronger emotional ties to rural areas may express stronger preferences for sustainable landscape features, such as renewable energy installations or biodiversity-promoting practices (Butler and Wärnbäck, 2019; Howley, 2011; Sayadi et al., 2009). Within this perspective, recent studies provide evidence that aesthetic values are systematically shaped by socio-demographic and cultural characteristics, though not always in uniform ways. Macaulay et al. (2025) show that age, gender, education, cultural background, and core nature values independently influence how people value green spaces, with systematic differences in emphasis on social, experiential, or natural attributes. Similarly, Kamičaitytė et al. (2019) show that professional background, environmental affinity, and lived experience shape landscape aesthetic judgments, with experts tending to prioritize ecological integrity and functional coherence, while lay publics place greater emphasis on visual harmony and recognizable landscape elements. Together, these studies indicate that aesthetic preferences are filtered through cultural norms, experiential familiarity, and value orientations, reinforcing the importance of accounting for heterogeneity when assessing landscape aesthetics.

Building on this literature, this study adopts a perception-based stated preference approach using digitally manipulated landscape images in a DCE. By presenting respondents with realistic visual representations of varying degrees of ecological management and infrastructural change, we aim to elicit nuanced aesthetic preferences that reflect both instinctive reactions to visual order and care, and more reflective experience-based interpretations of sustainability. This approach aligns with recent calls for integrative landscape assessment methods that bridge visual appearance and underlying management processes, while allowing empirical exploration of whether aesthetic values are broadly shared or context dependent across regions.

3. Methodology

3.1. Study area

Three distinct study areas are considered, namely Flanders (Belgium), Hungary and the UK (Figure 1). Covering 46% of the total Flemish land surface area (Statbel, 2022), land use patterns and agricultural activities in Flanders are highly clustered and regional (Figure 1). Though the Flemish rural landscape is typically a highly fragmented one, the Flemish agricultural sector has undergone a transition towards fewer and larger agricultural holdings since the 1990s (Department Landbouw en Visserij, 2020), resulting in increased evidence of consolidation of land use. From a policy perspective, Flanders is characterized by a highly regulated and spatially planned rural landscape, shaped by strong zoning instruments and dense settlement patterns. The extreme population densities means that agricultural land is under continuous pressure from urban expansion, infrastructure development, and competing land uses. As a result, agri-environmental-climate measures under the CAP in Flanders increasingly emphasize multifunctionality, landscape quality, and ecological connectivity (European Commission, 2025a). This makes Flanders a relevant case for examining how public preferences respond to ecological interventions in already highly managed and visually saturated landscapes.

Similarly to Flanders, the topographical diversity across Hungary has resulted in regional patterns of land use (Figure 1), while the historical context has driven the consolidation of agricultural plots into large homogenized agricultural landscapes. The Great Hungarian Plain is the main agricultural region in the country, dominated primarily by arable agriculture. The Hungarian policy and landscape context in quite unique within the EU. The legacy of collectivization and post-socialist land reforms has resulted in large-scale, visually homogeneous agricultural landscapes, where ecological features such as hedgerows and small landscape elements are comparatively scarce (European Commission, 2025b). Landscape planning regulations and public discourse around landscape aesthetic have historically played a less prominent role than in Western European countries. As a result, Hungary provides an interesting comparison for assessing whether aesthetic preferences for more ecologically complex landscapes emerge even where such features are less common and culturally embedded.

Of the total land area of the UK, comprised of England, Scotland, Wales and Northern Ireland, roughly 75% is dedicated to agricultural activities (RSPB, 2022). As seen in Figure 1, agricultural activities are spread throughout the entirety of the UK, though livestock (primarily sheep grazing) is concentrated mostly in Wales, Northern Ireland and Scotland, while arable agriculture is typical for the eastern and south-eastern regions of England (RSPB, 2022). The UK represents a third, distinct case study in which agricultural landscapes are strongly embedded in heritage, conservation, and amenity-oriented planning frameworks. Following Brexit, the UK has moved away from CAP-style area-based payments towards agri-environmental schemes that explicitly incentivize the provision of public goods. Landscape aesthetics are therefore not only a social concern but also explicit policy objective, particularly in England's Environmental Land Management schemes (DEFRA, 2024). The inclusion of this study area allows us to explore whether stated preferences align with emerging policy narratives.

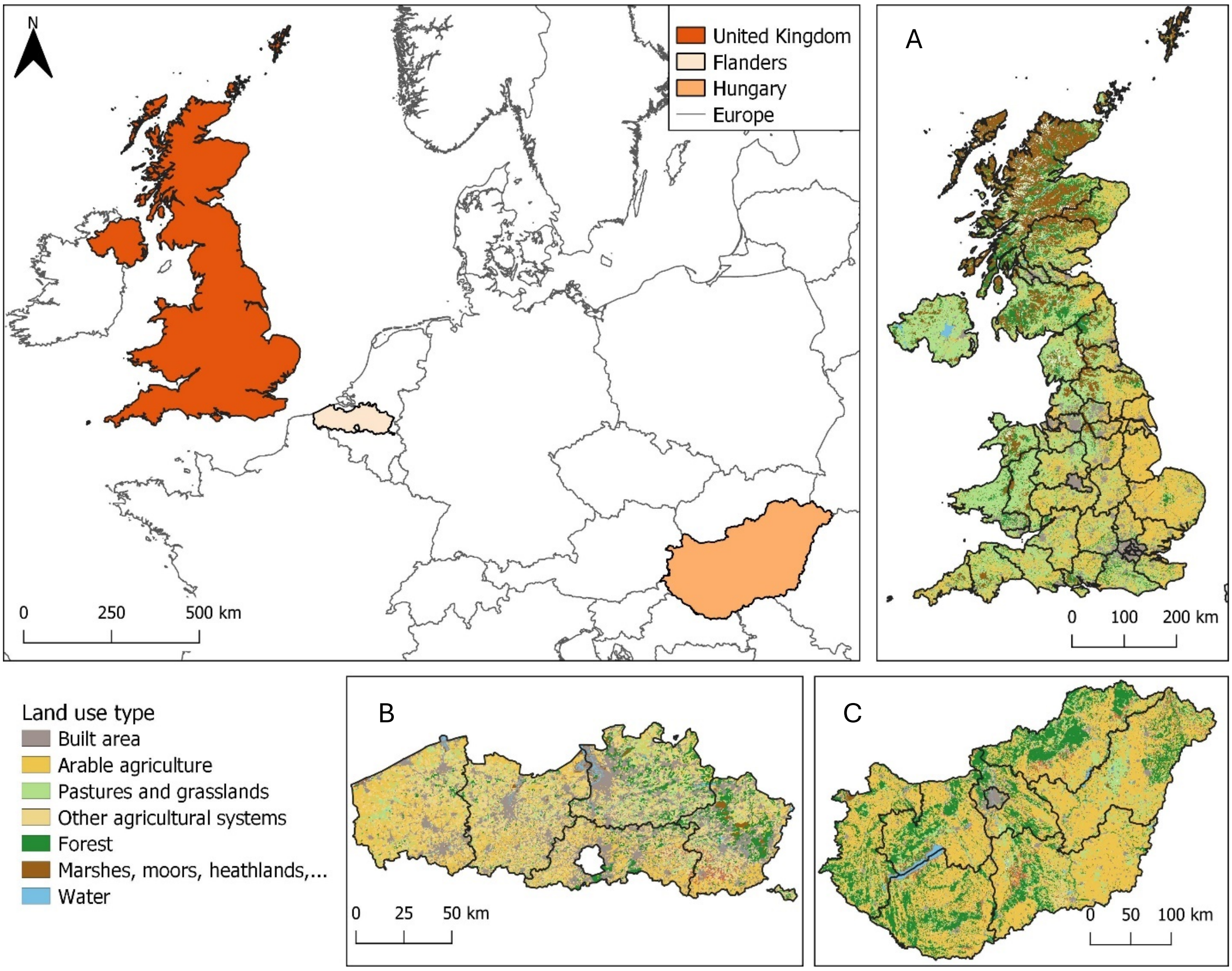

Figure 1. Overview of the study areas A) the United Kingdom, B) Flanders, Belgium, and C) Hungary, and their land use.

3.2. DCE design and survey

The DCE methodology has been widely used in studies evaluating the aesthetics of rural landscapes (summarized in Table A1 in the appendix). Based on an evaluation of this body of literature, we compiled a comprehensive list of visual landscape attributes associated with the adoption of more environmentally friendly farming practices. Table A1 in the Appendix shows the attributes used in the different studies considered in this literature search. Most studies evaluating preferences for landscape aesthetics were found to consider landscape elements associated with small landscape features (e.g., hedges), soil conservation practices (e.g., soil cover and tillage), green energy infrastructure (e.g., presence of wind turbines), and diversified farming systems (e.g., species diversity and variation in landscape mosaic). This initial list of attributes was refined according to three criteria: (i) applicability to a mixed arable-livestock agricultural context, (ii) relevance across the three study areas, and (iii) ability of the attribute levels to reflect varying degrees of ecological transition (defined by the different levels of the attributes).

To ensure both ecological relevance and stakeholder validity, the refined list was evaluated through expert consultation in each study region and through a pilot exercise with 32 respondents from the target population. This process resulted in the final set of seven attributes (six categorical, and one continuous payment vehicle), each representing the visual impact of more environmentally friendly practices on a landscape, while the levels reflect the degree to which the implemented practices are more or less ecological, ranging from intensive conventional to more diversified and extensive. A detailed description of each attribute is provided in Table 1.

As a payment vehicle we include an increase in the monthly price of a typical household food basket reflecting additional costs accrued by farmers for incorporating more environmentally friendly farming practices. In designing a DCE intended to compare preferences and WTP across three distinct European study areas, a universally applicable and easily interpretable payment vehicle was required. Food expenses represent a regular and salient household expenditure in all study areas, providing a concrete and relatable framing of the potential financial implications of more ecological farming practices. We acknowledge that agricultural landscapes provide both use and non-use values, and respondents may value landscape aesthetics independently of whether the food they consumer is produced locally. However, linking the payment vehicle to food costs has two advantages. First, it provides a transparent mechanism for cost transfer that reflects the economic reality that a transition towards more ecological production entails higher production costs, partially born by consumers. Second, evidence shows that more tangible and personally relevant payment vehicles can reduce protest behaviour and enhance perceived consequentiality compared to less direct instruments such as general taxes or one-off payments (Carneiro and Carvalho, 2014; Taylor et al., 2010). Nonetheless, we recognize that this payment vehicle captures only part of the broader set of values associated with landscapes, and may not explicitly represent non-use values.

To facilitate comparison between the countries and account for differences in purchasing power parity (PPP), the monetary attribute was expressed in PPP corrected euros (PPP €) prior to econometric analysis. In the Flemish and Hungarian case studies, PPP was accounted for ex-ante when establishing the payment vehicle levels by considering a 1%, 2.5%, 4% and 5% increase from the local average monthly household expenditure of food and non-alcoholic beverages (€383 in Flanders and 90,000 Ft in Hungary). In the UK study area, PPP correction was done ex-post, with price levels expressed relative to the EU-27 PPP in 2020, which was 0.820708 (Eurostat, 2022), prior to analysis.

Table 1. Description of the attributes and levels used in the DCE. The base level of each attribute is indicated in square brackets.

Attribute	Definition	Levels
Land coverage	The way in which agricultural parcels within the landscape are covered between the harvest of a main crop and the sowing of the next crop. If not left bare, soils may be covered by a cover crop, crop residue, spontaneous growth or some other form of land coverage.	1. Bare land [base level] 2. No bare land
Landscape diversity	The variety and number of crops and grazing animals that are visible within an agricultural landscape.	1. Monoculture [base level] 2. Low diversity 3. Medium diversity 4. High diversity
Crop dividers	The visible separation between parcels (used for cropping and livestock grazing) within an agricultural landscape.	1. No visible separators [base level] 2. Wild, unmanaged separators 3. Clear, managed separators
Mechanisation level	The size of the machinery used on the farms that is visible within the landscape.	1. No mechanisation 2. Low mechanisation 3. Medium mechanisation

Attribute	Definition	Levels		
		4. High mechanisation [base level]		
Farm infrastructure	The size of the farm and its farm buildings that are visible within the agricultural landscape. Farm buildings include the farmstead, as well as any sheds, silos and other storage facilities.	1. Small buildings 2. Medium-sized buildings 3. Large buildings [base level]		
Energy generating infrastructure	The type, size, amount and distribution of the equipment used to generate energy placed on and surrounding the farmstead.	1. Solar panels on roofs [base level] 2. Solar panels on roofs and ground (medium) 3. Wind turbines (25m high) and solar panels on ground (high) 4. Wind turbines (>25m high) and solar panels on ground (very high)		
Increase in the monthly price of a food basket (per household)[A]	The increase in the typical monthly food expenditure for the household for the purchasing of food derived from more integrated landscapes.	5 EUR 10 EUR 15 EUR 20 EUR	580 HUF 1700 HUF 2600 HUF 3500 HUF	5 GBP 10 GBP 15 GBP 20 GBP

[A] The payment vehicle was expressed in local currency: Euro (EUR) in Flanders, Hungarian Forint (HUF) in Hungary and Pound Sterling (GBP) in the UK.

Directional priors obtained from the consultation with the target population were used in a D-efficient design using Ngene (ChoiceMetrics, 2012). In total, 18 choice cards of two hypothetical alternative agricultural landscapes and an opt-out were generated and grouped into two blocks of nine choice cards each. A dominance check was done to avoid dominant or unplausible scenarios. Landscapes in each choice card were visualised using photoshopped images created by a professional photographer/photo editor. To create the photorealistic images used in this study a master image of a farm in Southern England was selected for its potential to allow several changes to be made to the landscape while maintaining a satisfactory degree of realism. The same image was used across all three study areas[1] to facilitate the comparison of results. The aesthetic elements associated with the attributes were inserted, where possible, in the same position in each alternative scenario to maintain consistency (Figure 2). The attribute levels of the mechanization, farm infrastructure and energy generating infrastructure attributes were left to vary in size but not in number. In other words, the same number of tractors, farm buildings and/or energy generating infrastructure was shown but the size of each was changed between the levels.

[1] The ability of the master image to capture a local landscape in the Flemish and Hungarian study areas was explicitly validated during pilot through follow-up questions.

Figure 2. Example of three choice cards as depicted to respondents. Photos by Bip Mistry.

The DCE was embedded within a larger survey in which information was collected about respondents' environmental attitudes, the importance they place on local rural landscapes, place attachment, recreational habits, food purchasing behaviour and socio-demographic characteristics. Environmental attitudes were measured using the New Ecological Paradigm (NEP) scale as described by Dunlap et al. (2000). Using 15 questions answered based on a 5-point Likert scale ranging from completely disagree (1) to completely agree (5), the NEP scale measures anthropocentric (a mean score >3) and ecocentric (a mean score ≤3) attitudes. The importance respondents place on local rural landscapes was measured through six questions to which respondents answered using a 5-point Likert scale, ranging from completely disagree (1) to completely agree (5). Questions centered around the degree to which rural landscapes form part of the national identity, the importance of maintaining rural landscapes, and the connection between visual elements of a landscape and environmental concerns, amongst others. Place attachment was captured through multiple choice questions related to living environment and personal connection of the agricultural sector. Recreational habits were captured through a 5-point Likert-scale question related to frequency of engaging in nature-related activities such as gardening and jogging. Information on food purchasing behaviour was collected through multiple choice questions related to frequency of purchasing organic products, where food products are more commonly purchased (supermarket, farmers market, etc.), dietary habits, and estimated average monthly household expenditure on food and non-alcoholic drinks. Lastly, socio-demographic information such as age, gender, education and income level, working status, and household size were collected through multiple choice questions. The full survey can be found in supplementary materials.

Prior to carrying out the DCE, respondents were informed of the aims of the research, i.e., to explore preferences for rural landscapes shaped by the movement towards 'ecological agriculture', defined as landscapes in which the various functions of agricultural (ecological, landscape, environmental management, food production and rural employment) are coordinated. After describing each attribute individually (using the descriptions provided in Table 1), respondents were asked to identify which of the two presented landscapes they preferred based on their visual characteristics. They were also given the opportunity to select the opt-out, which reflected a choice for neither of the presented landscapes.

3.3. Sampling and data cleaning

The DCE was carried out online in February 2022. Respondents were randomly selected through two market research agencies (Bilendi in Flanders, and Qualtrics in Hungary and the UK). The final sample was composed of 836 respondents; 345 in Flanders, 169 in Hungary and 322 in the UK. Though the use of a market research agency for sample selection may increase the risk of compensation and self-selection bias (Börger, 2016), we requested representativeness of the sample based on age, gender, and education level for each study area. The panels used in both market research agencies were recruited through a multi-sourcing strategy to avoid sampling bias. This involved respondent recruitment through third party databases, banner media websites, and the agency's websites amongst other approaches. To further avoid bias, registered panel respondents are invited through e-mail to partake in an individual survey and were not given any information regarding the content of the survey prior to partaking in it. As a renumeration strategy, respondents receive points which can be saved up and swapped for prizes. Points are kept to a minimum so as to avoid 'professional respondents'.

Respondents were encouraged to answer the questions as truthfully as possible, though a cheap-talk script was not incorporated in the survey to avoid overburdening respondents with information. Instead, questions related to certainty and attribute non-attendance were incorporated in the survey to check for bias and consequentiality *ex post*. Next to this, the survey was timed in order to identify potential professional respondents.

Only respondents aged 18 and over could complete the survey. Prior to analysis, all true protest responses as well as respondents who took more than 1440 minutes (24 hours) and less than 3.5 minutes to complete the survey were removed from the sample. These values were identified as cut-offs based on the distribution of completion time in minutes across the sample as well as authors' own interpretation. Protest responses were identified based on the systematic selection of the opt-out across all choice tasks. For those who did so, a follow-up question was included to identify true protest responses by inquiring why they systematically selected the opt-out. Those who indicated "prefer not to say", "I did not understand what was expected of me", "I could not visualize some or all of the attributes" and "I do not like this survey" were removed as true protesters. In all, a total of 54 respondents were removed from the Flemish sample, 11 from the Hungarian sample, and 6 from the UK sample prior to analysis.

3.4. Analytical framework

Analyses were performed using Stata 17 (StataCorp, 2021). First, we assess regional differences in landscapes by estimating a generalized multinomial logit (G-MNL) model with interaction-effects for the study regions. Second, we estimate region-specific mixed logit (MXL) models in WTP-space. Third, we use a latent class (LC) estimation to explore heterogeneity in taste amongst respondents and the characteristics driving this heterogeneity.

To evaluate preference for, and the value of, landscape aesthetics, we carry out three distinct utility-based estimations. First, we use the G-MNL model to estimate differences in preferences between study areas, accounting for preference and scale heterogeneity associated with pooling samples from three distinct study areas, thus improving on the simpler MXL model (Fiebig et al., 2010). We estimate a model with two dummy-coded interaction effects coded for the Hungarian and UK study areas. All main effects were kept random, assuming a normal distribution for all. Interaction effects between the main effects and the dummies were kept fixed. In our estimation, the utility (U_{ijt}) derived by individual i from choosing an alternative j in choice card t is defined as:

$$U_{ijt} = \alpha_i OO + \beta_i x_{ijt} + \theta_i (SA * x_{ijt}) + \varepsilon_{ijt} \tag{1}$$

$$\beta_i = \sigma_i \beta + \gamma \eta_i + (1 - \gamma) \sigma_i \eta_i$$

$$\theta_i = \sigma_i \theta + \gamma \xi_i + (1 - \gamma) \sigma_i \xi_i$$

where x_{ijt} is the vector of attributes, β_i the vector of individual-specific main effects, θ_i the vector of individual-specific interaction effects for study area (SA) dummy, and ε_{ijt} is the idiosyncratic error assumed to be i.i.d. The specification of β_i depends on i) β, a vector of mean attribute utility weights, ii) the individual-specific scale of the idiosyncratic error (σ_i) with $\sigma_i \sim LN(1, \tau)$, and iii) η_i, the vector of individual n-specific deviations from the mean assumed to be multivariate normal.

The individual-specific scale parameter can be specified as:

$$\sigma_i = \exp\left(\bar{\sigma} + \delta Z_i + \tau \eta_i\right) \tag{2}$$

where we assume $\bar{\sigma} = {}^{-\tau^2}/_{2}$, and τ is the standard deviation of the scale. The vector Z_i contains the observed individual characteristics that explain between-individual differences in scale, with δ the corresponding vector of coefficients (Eppink et al., 2019). In our estimation, Z_i is identified as the study area. The parameter that governs the variance of residual taste heterogeneity with scale, $\gamma \in [0,1]$, is assumed to be 0 (Fiebig et al., 2010; Hess and Train, 2017).

Second, we estimate a MXL model in WTP-space as defined by Train and Weeks, (2005) to identify respondents' WTP for the different attribute levels in each study area. Separating price (p) and non-price (x) attributes, utility in WTP-space is written as:

$$U_{ijt} = \alpha_i OO - \lambda_i p_{ijt} + (\lambda_i w_i)' x_{ijt} + \varepsilon_{ijt} \tag{3}$$

Here, $\lambda_i = ({}^{\theta_i}/_{\sigma_i})$ is the ratio of the price coefficient to the scale parameter and $w_i = {}^{c_i}/_{\lambda_i}$. $c_i' = ({}^{\beta_i}/_{\sigma_i})$ is a vector of the ratios of the non-price attributes to the scale parameter. WTP values were obtained through a split-sample estimation (by study area) in which the payment vehicle followed a log-normal distribution, while all remaining parameters were assumed to follow a normal distribution. We used the method proposed by (Poe et al., 2005) to test for differences in WTP estimates between the three study areas.

Finally, we estimate a LC model with four classes in which respondents are assigned to a class based on probabilities derived from preference estimates. The optimal number of classes (four) was selected based on the Bayesian Information Criteria (BIC), the Consistent Akaike Information Criteria (CAIC), and the meaningful interpretation of results (Pacifico and Yoo, 2013; Yoo, 2019). Study area, socio-demographic, attitudinal and recreational characteristics of respondents were compared between classes using a one-way ANOVA for continuous variables and a chi-squared test for categorical variables.

4. Results

4.1. Descriptive statistics

The socio-demographic and attitudinal characteristics of the study area-specific samples ($N_{Flanders} = 345, N_{Hungary} = 169, N_{UK} = 322$) most important for the interpretation of the results are presented in Table 2. The remaining characteristics are detailed in Tables A2 and A3 in Appendix A. Notably, respondents tended to be younger and more highly educated than the general population, likely due to the online sampling strategy, which should be considered when interpreting results. Significant socio-demographic differences between the study areas were observed for age, education, living environment, and connection to agricultural landscapes. The UK sample had the highest mean age (53 years) and the lowest education levels, with 45% holding a secondary degree or lower. In contrast, the Flemish sample was the most highly educated, with 53% having a master's degree or higher, and had the largest share of rural residents (48%). The Hungarian sample was predominantly urban (67%), yet respondents had a stronger connection to agricultural landscapes. The UK sample was more evenly distributed across urban (40%), peri-urban (36%), and rural (24%) environments.

Despite the noted socio-demographic differences between the samples, attitudinal characteristics were largely similar; dominated primarily by eco-centric environmental attitudes as demonstrated by the mean NEP score ($\overline{NEP}_{pooled} = 3.67, NEP\sigma_{pooled} = 0.57$) and a high importance placed on well-maintained local rural areas ($\overline{NEP}_{pooled} = 4.00, NEP\sigma_{pooled} = 0.54$).

Table 2. Socio-demographic characteristics of the pooled sample and sub-samples. Significant differences between sub-samples are indicated in columns seven to nine.

		Sub-samples			Sub-sample differences		
Characteristic	**Pooled sample**	**Flanders (1)**	**Hungary (2)**	**United Kingdom (3)**	**1-2**	**1-3**	**2-3**
Size (n)	836	345	169	322			
Gender (% female)	49.16	52.46	42.60	49.07			
Mean age (min, max)	50.45 (18, 89)	50.19 (18, 85)	45.81 (18, 76)	53.19 (18, 89)	**	*	*
Education (%)							
Low (secondary degree or lower)	39.95	33.04	35.51	45.03		**	
Medium (bachelor degree)	17.82	14.20	25.44	17.70	**		
High (master's degree or higher)	42.22	52.75	39.05	32.61	**	***	
Net household income/month (%)							
Below average	25.36	13.91	37.27	26.04	**	***	*
Around average	15.19	13.62	23.08	12.73	**	**	
Above average	43.03	47.25	40.24	40.06			
Living environment (%)							
Urban (city or town)	37.92	21.74	67.46	39.75	***	***	***
Peri-urban	30.38	30.14	19.53	36.34			***
Rural	31.70	48.12	13.02	23.91	***	***	*
Connection to agricultural landscape (%)							
Personally (or direct relations) work/have worked in the agricultural sector	7.54	6.09	14.20	5.59	**		**
Live/have lived in a rural area	26.91	30.72	37.28	17.39		***	***
Frequently visit rural areas for leisure activities	20.57	17.10	31.36	18.63	***		**
New Ecological Paradigm (NEP) score (mean, σ)[A]	3.67 (0.57)	3.60 (0.55)	3.80 (0.56)	3.69 (0.60)	*		
Importance of local rural landscapes (mean, σ)[A]	4.00 (0.54)	3.95 (0.56)	4.04 (0.55)	4.00 (0.51)			

Note: Significance is indicated with * $p<0.05$, ** $p<0.01$, or *** $p<0.001$.

[A] The New Ecological Paradigm (NEP) scale and the importance of local rural landscapes are measured on a 5-point Likert scale (1 = completely disagree, 5 = completely agree).

The median time taken to complete the survey was 15 minutes. Comparing between the study areas we find that the Hungarian sample took slightly longer (18 minutes), while the Flemish and UK samples both had a median completion time of 14.5 minutes. Follow-up questions were included related to choice certainty and attribute non-attendance to assess validity of the DCE estimates. Choice certainty was measured on a scale of 1 (very uncertain) to 5 (very certain). The mean certainty across the sample was 3.33, indicate relative degrees of certainty. UK respondents are somewhat more certain ($\bar{x} = 3.46, \sigma = 0.80$), followed by both Hungarian respondents ($\bar{x} = 3.25, \sigma = 0.78$), and Flemish ($\bar{x} = 3.25, \sigma = 0.81$) respondents. This degree of certainty is also reflected in the self-reported attribute non-attendance rates, with a Kruskall-Wallis test confirming that UK respondents had a significantly lower non-attendance rate than the Hungarian and Flemish respondents ($p = 0.001$).

Of the full sample, 64.35% of respondents indicated not attributing to at least one attribute. On average, respondents in the Flemish sample stated not attending to 1.37 attributes. In the UK sample the mean number of attributes not attended was 1, while in the Hungarian sample this was 1.34. From Table 3 we note that non-attendance rates are rather high. However, respondents are notably not able to accurately self-report non-attendance (Caputo et al., 2018; Scarpa et al., 2013). This is reflected in the non-attendance rates of the payment vehicle, which are the highest across all attributes. However, of those self-reporting not attending to the payment vehicle, 87% indicated doing so because they did not find the attribute important in an agricultural landscape. This indicates that respondents found this attribute less important in their decision making, but does not indicate they fully ignored it. As such, we do not account for self-reported attribute non-attendance in the analysis, but we are careful in the interpretation of the WTP estimates in light of this.

Table 3. Attribute non-attendance shares (%) per attribute

Attribute	Full sample (%)	Flanders (%)	Hungary (%)	UK (%)
Land coverage	17.46	19.42	20.71	13.66
Landscape diversity	13.16	16.81	8.28	11.80
Crop dividers	14.83	16.81	18.34	10.87
Mechanisation	13.28	15.07	14.76	10.56
Farm buildings	16.15	18.26	18.34	12.73
Energy generating infrastructure	19.14	20.58	20.12	17.08
Price	26.44	29.86	33.73	18.94

4.2. Positive preferences for landscape aesthetics from more environmentally friendly practices

The main effects estimated in the G-MNL model with interaction-effects for study area (Table 4) demonstrate that the Flemish respondents have a significant positive preference for increased levels of landscape diversity, for the incorporation of both wild, unmanaged and clear, well-managed crop dividers, and for a shift from low (solar panels on roofs) to very high (wind turbines >25m high and solar panels) levels of energy generating infrastructure. Simultaneously, we find significant negative preferences for a shift from large to small mechanization levels, as well as for a shift from large to small infrastructure levels. Lastly, Flemish respondents hold a significant negative preference for the opt-out as well as the payment vehicle, illustrating that respondents prefer landscape aesthetics associated with a minimal degree of ecological transition, but have an aversion to increased food prices associated with this.

Table 4. G-MNL model with Flanders as main effects and Hungary and UK as interaction effects. Payment vehicle (price), which represents a price increase in an average monthly household food basket) is expressed in purchasing power parity euros (PPP €).

	Main effects		Interaction effects	
Attributes	β	σ	$\beta_{Hungary}$	β_{UK}
Opt-out (dummy)	-10.315***	5.685***	1.542**	2.286***
Opt-out (effects)	-9.284***	4.603***	1.047	0.808
Land coverage [None]				
Covered	-0.080	0.060	0.120	0.121
Landscape diversity [Monoculture]				
Low	1.420***	0.362***	-0.661***	-0.673***
Medium	2.086***	0.162*	-0.987***	-0.872***
High	2.649***	0.351**	-1.373***	-0.775***
Crop dividers [None]				
Wild, unmanaged	0.312**	0.047	-0.143	-0.102
Clear, well-managed	0.620***	0.211***	-0.212	-0.031
Mechanisation levels [High]				
Medium	-0.924***	0.194*	0.487	0.417
Low	-0.482*	0.046	0.163	0.231
None	-0.610**	0.039	0.394	0.170
Farm infrastructure [Large]				
Small	-0.346*	0.091	0.389	0.089
Medium	-0.636***	0.159**	0.634**	0.214
Energy generating infrastructure [Low][A]				
Medium	-0.127	0.100	0.227	0.232
High	-0.009	0.039	0.250	0.179
Very high	0.519***	0.432***	-0.226	-0.169
Price (PPP €)	-0.192***	0.179***	0.093***	0.022
δ **(Hungary)**	0.347**			
δ **(UK)**	0.216*			
τ	1.045***			
N	22572			
Log-likelihood	-5331.88			
AIC	10797.76			
BIC	11335.40			

Note: Significant coefficients are indicated with *p<0.10, **p<0.05, ***p<0.01. The reference level of each attribute is indicated in square brackets.

[A] Levels for the attribute *Energy generating infrastructure* have been coded as *Low* (solar panels on roofs), *Medium* (Solar panels on roofs and ground), *High* (Solar panels on roofs and ground + wind turbines <25m high), and *Very high* (Solar panels on roofs and ground + wind turbines >25m high).

The interaction effect coefficients reported in Table 4 demonstrate limited significant differences in preferences between the study areas. Indeed we see that, on the whole, the magnitude of the preferences change rather than their sign. UK respondents have significantly smaller negative preferences for the opt-out, as well as smaller positive preferences for increased levels of landscape diversity compared to the Flemish sample. While similar differences are observed between the Flemish and Hungarian samples, respondents in the Hungarian sample also have significantly larger preferences for a shift from large to medium levels of infrastructure, as well as a smaller aversion towards increased price levels. Dummy-coded OO coefficients indicate respondents prefer one of the presented alternatives over the opt-out. Interaction-effects indicate that this preference is slightly less negative in Hungary and Flanders, though the effects-coded model indicates no significant difference. Re-estimating the model with interaction effects for Flanders and the UK (results in Appendix B, Table B1) shows differences in preferences between the UK and Hungarian respondents only for the price attribute (significantly less negative in UK) and high levels of landscape diversity (significantly more positive in UK). Hungarian respondents thus hold, though only for limited attributes, different preferences for landscape aesthetics compared to Flemish and UK respondents.

In line with the preference estimates, we find largely similar WTP estimates across the different study areas (Figure 3; full model output is described in Appendix B, Table B2). Overall, respondents across all three study areas are willing to pay for increased levels of landscape diversity, the integration of clear, well-managed crop dividers, and for a shift from low to very high levels of energy generating infrastructure. With the exception of a significant negative WTP for a shift from large to medium farm infrastructure in Flanders, and a significant positive WTP for a shift from low to very high energy generating infrastructure in both Flanders and Hungary, the WTP for the remaining attribute levels are insignificant.

Though the direction of the WTP coefficients is largely similar between study areas, their magnitude differs slightly. Specifically, we find that Flemish respondents are willing to pay more for increasing levels of landscape diversity than Hungarian and UK respondents ($p < 0.05$). Flemish respondents are willing to face increased food basket prices between 8.75 PPP € (for low diversity) and 15.38 PPP € (for high diversity) per month to see a shift away from monoculture reflected in landscape aesthetics. Comparatively, respondents in Hungary and the UK are willing to pay much less for this. Lastly, we find that Hungarian respondents are willing to pay significantly more for a shift from low to high levels of energy generating infrastructure than UK respondents (p<0.05)[2].

[2] The Poe-test relies on asymmetrical confidence bounds to compute significant differences, while the MXL model estimated in WTP-space relies on symmetrical bounds to calculate 95% confidence intervals, resulting in a mismatch between significant differences in WTP found between countries using the Poe-test and the 95% confidence intervals indicated in Figure 3.

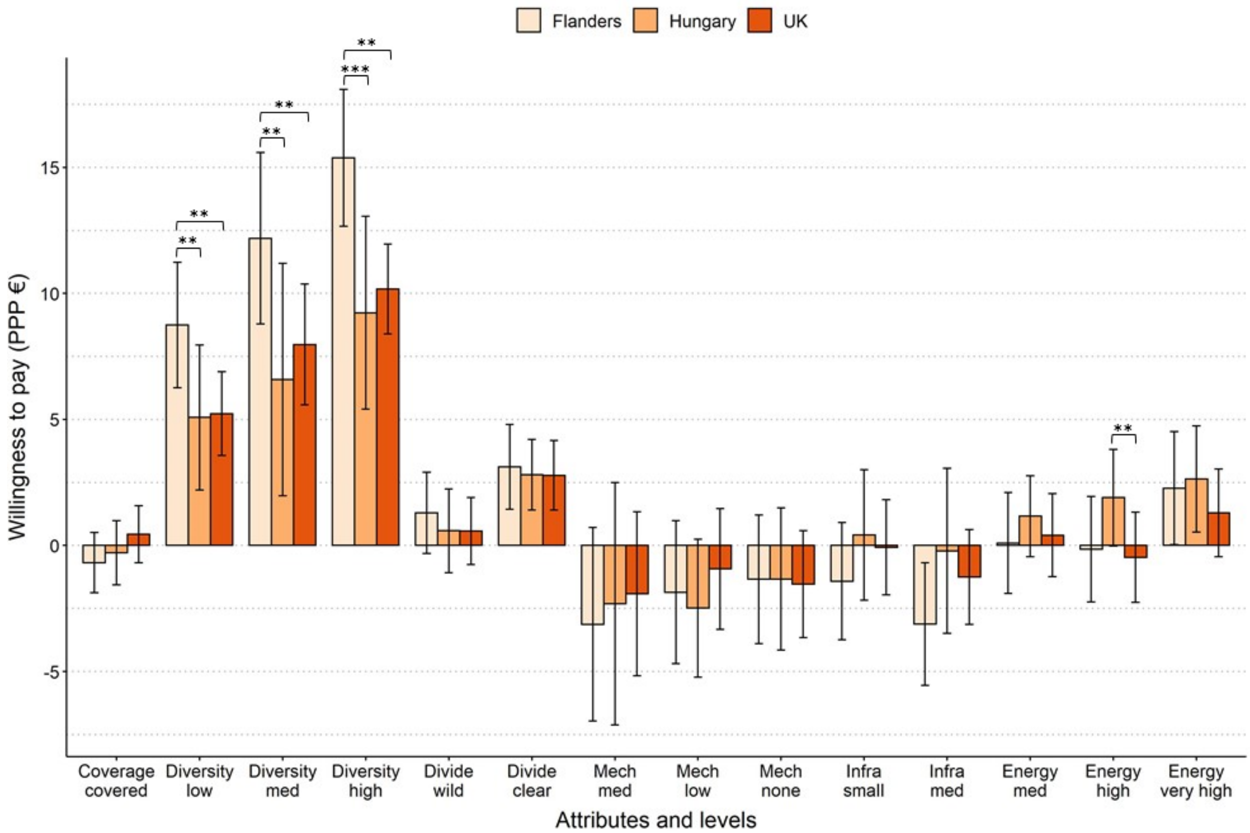

*Figure 3. Willingness to pay (WTP) (PPP €) for attributes associated with aesthetic landscape features. Error bars represent 95th percent confidence intervals. Significant differences between study areas are indicated as *p<0.10, **p<0.05, ***p<0.01.*

4.3. Cross-country preferences

To explicitly account for preference heterogeneity we estimated a latent class model on the pooled sample (Table 5). A model with four classes was found to have the best fit based on information criteria and overall interpretability of results. Across the four classes, respondents differ primarily in how they reconcile ecological enhancement with visible agricultural management and infrastructure. The largest share of respondents are found in Class 3 ($n = 355$). These individuals strongly favor increased landscape diversity while simultaneously rejecting reductions in farm infrastructure, indicating support for ecological enhancement that remains visibly embedded within productive agricultural systems. As such, we refer to respondents in this class as *landscape pragmatist*; their preferences seem to marry ecological performance with evidence of agricultural intervention.

Table 5. Latent class parameter estimates for four latent classes.

Attributes	Class 1 (β)	Class 2 (β)	Class 3 (β)	Class 4 (β)
Opt-out (dummy)	-2.853***	-3.454***	-2.779***	0.571
Opt-out (effects)	-2.568***	-5.147***	-4.398***	0.037
Land coverage [None]				
Covered	-0.052	-0.048	-0.130	0.224
Landscape diversity [Monoculture]				
Low	-0.006	0.638***	1.578***	0.283
Medium	0.041	0.757***	2.129***	0.619*
High	0.279*	0.306	2.939***	1.056***
Crop dividers [None]				
Wild, unmanaged	0.325***	-0.217	0.028	0.105
Clear, well-managed	0.560***	-0.147	0.423***	0.403
Mechanisation levels [High]				
Medium	-0.798***	1.379***	-0.388	-0.394
Low	-0.587***	0.828**	-0.008	0.001
None	-0.594***	1.077***	0.085	-0.170
Farm infrastructure [Large]				
Small	-0.266**	0.628**	-0.324*	-0.102
Medium	-0.530***	0.895***	-0.360*	-0.038
Energy generating infrastructure [Low][A]				
Medium	-0.119	0.387*	0.246	0.064
High	0.097	0.013	0.241*	-0.131
Very high	0.535***	-0.068	0.225	-0.133
Price (PPP €)	-0.024**	-0.312***	-0.078***	-0.164***
N	22572			
Log-likelihood	-5356.903			
AIC	10847.81			
BIC	11385.44			
CAIC	11217.67			

Note: Significant coefficients are indicated with *p<0.10, **p<0.05, ***p<0.01. The reference level of each attribute is indicated in square brackets.

[A] Levels for the attribute *Energy generating infrastructure* have been coded as *Low* (solar panels on roofs), *Medium* (Solar panels on roofs and ground), *High* (Solar panels on roofs and ground + wind turbines <25m high), and *Very high* (Solar panels on roofs and ground + wind turbines >25m high).

The second largest class, Class 1 ($n = 241$) is typified by respondents with an appreciation of aesthetics associated with well-managed landscapes, as demonstrated by their positive preferences for crop dividers (more so for clear, well-managed dividers) and negative preferences for reduced levels of mechanization and infrastructure. Visible stewardship is central to their aesthetic valuation. We thus refer to respondents in Class 1 as *landscape stewards*. Compared to the other classes, *landscape stewards* seem more focused on the aesthetic signals of care, continuity, and cultural management embedded in agricultural landscapes than ecological diversity in itself.

Class 2 ($n = 172$), referred to as *landscape idealists*, is typified by respondents who prefer less evidence of stewardship, instead expressing a more normative and aspirational vision of ecological transition. This is reflected in their positive preferences for increased landscape diversity and energy generating infrastructure, as well as for reduced levels of mechanisation and farm infrastructure. Their positive perception of energy-generating infrastructure suggests an orientation toward symbolic markers of sustainability rather than traditional signs of agricultural stewardship. Overall, their preferences align with a more romanticized vision of environmentally-friendly agricultural landscapes. Lastly, Class 4 ($n = 68$) is characterized by respondents with weakly articulated landscape preferences. Respondents in this class show no significant preference for opting into depicted landscapes and only consistently value medium and high levels of landscape diversity. We therefore refer to respondents in Class 4 as *impartialists*.

Respondents' socio-demographic, attitudinal, and recreational characteristics (Appendix B, Table B3) are compared between the four latent classes to identify whether these explain characterisations as *landscape stewards*, *idealists*, *pragmatists* or *impartialists*. While little differentiation emerges based on study area, gender, and age, more pronounced differences are observed in education, income, environmental attitudes, and experience with agricultural landscapes. Across all dimensions, *impartialists* (Class 4) stand out as the most distinct group. Respondents in this class are on average lower educated, less economically secure, and less connected to agricultural landscapes. They also express more anthropocentric environmental attitudes and are less convinced that agriculture can play a meaningful role in achieving sustainability goals. Consistent with their weak preference structure in the DCE, *impartialists* attach relatively low importance to rural landscapes as part of local identity and place less value on openness, depth, and wilderness in agricultural landscapes. Taken together, these characteristics suggest that agricultural landscapes hold low personal importance for this group, helping to explain their general indifference toward the landscape configurations presented in the choice tasks.

By contrast, respondents in Classes 1, 2 and 3 share a higher degree of engagement with and valuation of agricultural landscapes, but differ in how this engagement is interpreted and translated into aesthetic preferences. *Landscape pragmatists* (Class 3) are most strongly anchored in lived and place-based experiences with agricultural landscapes. They tend to be relatively highly educated and more likely to report direct connections to the agricultural sector. They place the greatest importance on local rural identity and emphasize landscape coherence and balanced land uses. These characteristics align with their preferences for landscapes that combine ecological diversity with visible agricultural structure, reflecting an interpretive frame in which sustainability and productivity are complementary rather than opposing. *Landscape stewards* (Class 1) are distinguished less by socio-economic position and more by patters of everyday engagement with rural landscapes. They report significantly higher participation in outdoor recreational activities than respondents in Classes 2 and 4. Interestingly, *stewards* report a weaker perceived connection with nature since the COVID-19 pandemic compared to the other classes, suggesting that their preferences may be grounded more in habitual landscape use and stewardship norms than in abstract environmental identification. *Landscape idealists* (Class 2) are notably less likely to report a personal connection to agricultural landscapes than *pragmatists*, perhaps explaining their preference for reduced visible intervention and stronger support for symbolic sustainability features such as renewable energy infrastructure.

Overall, the latent class results reveal that preference heterogeneity is not primarily driven by socio-demographics (as supported by the G-MNL models estimated with interaction effects for the above-mentioned respondent characteristics, reported in appendix Tables B4-B6), but rather by differences in landscape salience, experiential proximity to agriculture, and interpretive frames of sustainability.

5. Discussion

This study aimed to assess how individuals value the aesthetic features of landscapes shaped by varying levels of ecological management in an attempt to quantify the co-benefits associated with the incorporation of more environmentally friendly management practices in an agricultural landscape. Our findings reveal strong public appreciation for the aesthetic value of agricultural landscapes that incorporate more environmentally friendly practices. Particularly elements such as increased landscape diversity and crop dividers are positively perceived, reflecting a preference for visually complex rural landscapes. These findings align with previous literature, which consistently links landscape complexity with higher perceived visual quality (Arnberger and Eder, 2011; Fry et al., 2009), and with more recent work showing that diversity, coherence, and visible ecological features are central components of perceived visual quality in agricultural landscapes (Albaladejo-García et al., 2023; Schirpke et al., 2023). Preferences for these landscape elements suggest that people favor landscapes that exhibit clear signs of stewardship, reinforcing the idea that visual cues of land care contribute positively to public perception.

While we find that landscape elements with a strong natural component (i.e., diversity and crop dividers) are most consistently preferred, our results also illustrate that infrastructure-related elements, such as farm infrastructure, mechanization, and energy generating infrastructure, are generally accepted as integral to modern rural landscapes. However, preferences for the degree of incorporation into the landscape of these elements vary. Notably, we find a lack of aversion to energy generating infrastructure, particularly at high levels. This suggests that respondents recognize the multifunctional role of agricultural landscapes, beyond food production alone, in contributing to broader sustainability objectives. This interpretation is consistent with evidence showing that renewable energy infrastructure can be more readily accepted in agricultural settings hen perceived as functionally integrated and when it helps avoid impacts on more natural protected landscapes (Salak et al., 2022). These insights highlight the need to balance between functionality and aesthetic management in rural land-use planning rather than assuming an inherent conflict between infrastructure and landscape appreciation.

We find that study region does not adequately explain the variation in preferences observed. Instead, as is supported by other studies, environmental attitudes and awareness (Howley, 2011), place attachment (Butler and Wärnbäck, 2019), and education level (Arnberger and Eder, 2011) most strongly influence preference formation. This pattern is consistent with recent empirical work showing that socio-demographic and cultural factors primarily shape how individuals interpret and weight landscape attributes, rather than producing fundamentally different aesthetic ideals across regions (Cai et al., 2022; Kamičaitytė et al., 2019; Macaulay et al., 2025). The latent class results suggest that preference heterogeneity is therefore less about geographically distinct landscape ideals and more about how individuals interpret and prioritize ecological quality, management intensity, and symbolic evidence of sustainability. Rather than reflecting fundamentally different visions of desirable agricultural landscapes, the three dominant preference groups share a broad appreciation for ecologically complex landscapes but differ in how they reconcile environmental quality with visible signs of agricultural management and infrastructure. This pattern echoes findings from other landscape preference studies, which show that heterogeneous groups often diverge not in what they value, but in how strongly and through which visual cues those values are expressed (Albaladejo-García et al., 2023; Schirpke et al., 2023).

The presence of a relatively small but clearly differentiated group of impartial respondents further underscores that landscape aesthetics are not equally salient for all individuals. The characteristics associated with this group, i.e., lower socio-economic resources, weaker place attachment, and more anthropocentric environmental attitudes, suggest that indifference may reflect limited experiential or emotional engagement with agricultural landscapes rather than active opposition. Comparable findings in other landscape preference studies indicate that weaker landscape attachment and use, lower nature connection, and fewer place-based experiences are associated with flatter preference structures and reduced sensitivity to visual change (Albaladejo-García et al., 2023; Macaulay et al., 2025; Schirpke et al., 2023).

Despite regional differences in historical and legislative rural context, we find no significant variation in aesthetic preferences or WTP estimates across the study regions. The fact that education, environmental attitudes, and place attachment most strongly explain class membership in the latent class analysis aligns with previous findings that aesthetic preferences often emerge from a combination of intuitive, affective responses and accumulated experiences rather than from socio-demographic characteristics alone (Arnberger and Eder, 2011; Howley, 2011). Recent cross-cultural studies similarly suggest that while socio-cultural background conditions how people relate to landscapes, core preferences for complexity and ecological coherence tend to be robust across contexts (Cai et al., 2022; Medeiros et al., 2024). Results of our study thus seems to particularly align with the theoretical perspective that evolutionary and emotional responses, rather than socio-cultural and environmental contexts, primarily shape aesthetic preferences (Swaffield and McWilliam, 2013; Tribot et al., 2018). In support of recent academic insights (Schüpbach and Kay, 2024; Zhang et al., 2022), we thus find that ecologically complex landscapes hold broad appeal in distinct regions across Europe, reinforcing the relevance of EU-wide agri-environmental policies. While the literature suggests that difference in WTP can be shaped by socio-cultural and legislative factors (Gobster et al., 2007), our findings indicate that landscape preferences remain largely consistent within the study regions. However, given that our study regions are situated along an east-west axis, future research should explore potential variations along a north-south gradient, where climate and land-use traditions may play a more significant role in shaping landscapes and thus public attitudes.

5.1. Policy implications

Our results indicate that agricultural management practices associated with increased ecological complexity and visible stewardship tend to generate aesthetic co-benefits that are positively valued by the public. This finding lends support to the inclusion of cultural ecosystem services as a complementary consideration, alongside biophysical outcomes, within agri-environmental and rural policy frameworks. Importantly, the observed consistency of preferences across the three study areas suggests that certain practices, such as diversified cropping systems and the integration of renewable energy infrastructure, may deliver broadly comparable aesthetic co-benefits across different European contexts. This cross-regional alignment implies that, for a subset of widely implemented management practices, cultural co-benefits may be addressed through coherent policy design at higher governmental levels, rather than requiring fully decentralized or region-specific approaches.

At the same time, these aesthetic benefits should be interpreted as reinforcing, rather than substituting for, ecological objectives, and their relevance may vary across population groups depending on lived experience and engagement with agricultural landscapes. Our results point to the possibility that some management practices already supported under existing policy framework may deliver a broader bundle of co-benefits than is currently acknowledged. In this sense, cultural ecosystem services may be systematically underrepresented in the way compensation levels are calibrated, even when they arise as secondary outcomes of practices primarily justified on ecological grounds. Recognizing these additional benefits does not require redefining policy priorities, but may help refine how the societal value of certain interventions is understood.

Finally, the preference for visually coherent and diverse landscapes observed in this study lends support to landscape-level approaches to policy design. Evaluating farm management interventions in isolation may overlook the cumulative effects that emerge when practices are coordinated across neighboring farms. Alternative policy arrangements, such as collective or landscape-based agri-environmental schemes in countries like The Netherlands, illustrate how cooperation at the landscape scale can be incentivized through collective contracts. While such approaches are not without challenges, our findings suggest that they may be better aligned with how the public perceives and values agricultural landscapes, particularly when multiple ecosystems services, both ecological and cultural, are jointly produced.

5.2. Limitations

As with all stated preference techniques, the DCE methodology has inherent limitations that should be considered when interpreting the results. A first limitation relates to the use of static visual stimuli to represent agricultural landscapes (Svobodova et al., 2018). Landscape preferences are influenced not only by individual features but also by their spatial arrangement. For instance, wind turbines tend to be more readily accepted when viewed from a distance (Butler and Wärnbäck, 2019). The fixed vantage point used in the choice cards may therefore have influenced respondents' preferences. Future research could address this by utilizing virtual reality, which allows for dynamic visualizations from multiple perspectives and incorporates sensory elements like noise, providing a more immersive assessment of landscape aesthetics (Mokas et al., 2021; Patterson et al., 2017). A related limitation concerns the seasonal character of the depicted landscapes. Landscape perceptions are known to vary considerably across seasons, particularly in temperate regions where vegetation cover, color, and land-use visibly change throughout the year (Junge et al., 2015; Schüpbach et al., 2016; Xu et al., 2022). As the choice tasks represent a single, seasonally specific landscape, the resulting preference estimates and WTP estimates should be interpreted within this seasonal context and not generalized uncritically across the full seasonal cycle.

Beyond the visual representation, hypothetical bias constitutes an additional limitation. Respondents were asked to state preferences based on hypothetical scenarios and visual depictions alone, without facing real financial consequences. This issue is compounded by the choice of payment vehicle, which framed costs as increases in household food basket prices. While this mechanism offers practical advantages in terms of cross-country comparability and scenario plausibility, it may also contribute to biased WTP estimates. Hypothetical payment contexts can lead respondents to overstate their willingness to pay, particularly when the payment mechanism is perceived as inconsequential or weakly linked to the valued good (Svenningsen and Jacobsen, 2018).

Importantly, the selected payment vehicle may not fully capture the non-use values that individuals hold for agricultural landscapes. When payment mechanisms are perceived as tangential to these values or insufficiently fair, respondents may either ignore the cost attribute or engage in protest behavior (Carneiro and Carvalho, 2014). Empirical evidence supports these concerns. van Zanten et al. (2016) show that introducing a monetary attribute can substantially alter the trade-offs and that a non-negligible share of participants may disregard the payment vehicle altogether, potentially inflating WTP estimates. Similarly, Hassan et al. (2018) find that price sensitivity and protest responses increase when payment vehicles affect everyday consumer goods, as respondents may resist financial framing that feels disconnected from the underlying benefit. Taken together, these findings suggest that while the food basket payment vehicle is defensible in a comparative setting, it may also contribute to overstated WTP levels, warranting cautious interpretation of absolute values.

Finally, characteristics of the sample affect the ecological validity and generalizability of the findings. Recruitment through market research agencies is known to increase the risk of self-selection bias in stated preference studies, and online panels often overrepresent older and more highly educated individuals (Börger, 2016), a patterns also observed in our sample. As a result, respondents may be more engaged with environmental topics than the general population, potentially leading to an overestimation of support for environmentally friendly landscape features. Moreover, variations in sample size across study areas may further limit comparability. In Flanders, a smaller and more densely populated region, respondents may exhibit stronger place attachment than those in Hungary and the UK, which could influence preference intensity and WTP estimates. These sources of bias suggest that absolute WTP values may exceed true population averages and should therefore be interpreted with caution. Future research would benefit from more balanced sampling strategies across regions and from testing alternative payment vehicles that better accommodate non-use values and reduce hypothetical bias.

6. Conclusion

This study set out to assess public preferences for the aesthetic value of agricultural landscapes shaped by more environmentally friendly farming practices, and how these values vary across individuals and contexts. The results demonstrate broad public appreciation for landscapes that combine ecological complexity with visible signs of stewardship, particularly those characterized by greater diversity and well=integrated landscape elements. Acceptance of renewable energy and other infrastructure-related features suggests that agricultural landscapes are increasingly perceived as multifunctional spaces that deliver societal benefits beyond food production. Together, these findings indicate that more environmentally friendly management practices can generate aesthetic co-benefits that complement their biophysical outcomes, strengthening the overall societal vale of agri-environmental interventions.

At the same time, the identification of distinct respondent groups reveals the nuanced nature of landscape preferences. While the majority of respondents shared broadly similar aesthetic preferences across regions, a smaller group exhibited weak or indifferent responses, suggesting that the cultural co-benefits of landscape change are not universal and should not be overstated in policy design. These findings support the integration of cultural ecosystem services into agricultural policy frameworks and complementary. Rather than competing, objectives alongside biodiversity, soil health, and climate goals. By acknowledging both shared and heterogeneous preferences, this study contributes to a more nuanced understanding of how ecological management practices shape public perceptions of agricultural landscapes, and provides a foundation for future research exploring additional non-use values and landscape-scale approaches to policy design.

Declaration of generative AI and AI-assisted technologies in the writing process

During the Preparation of this work the author(s) used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/services, the author(s) reviewed and edited the content as needed and take full responsibility for the published article.

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Appendix A

Table A1. Summary of literature review.

Paper	Objective	Sample	Attributes (relevant to this study)	Images
Bernués et al., 2019 https://doi.org/10.1016/j.ecoser.2019.101002	Ecosystem services of multifunctional agriculture	General local population, region in Spain, Norway and Italy	- Abandonment/rich mosaic [cultural services] - Biodiversity (animals, plants, insects) [supporting services] - Number of fires, soil fertility levels, water quality [regulating services] - Quality products (like IGP) [provisioning services] - Monetary: Tax (10 to 180 EUR)	Yes
Castillo-Eguskitza et al., 2019 https://doi.org/10.1016/j.landusepol.2019.104200	Preference for ecological management scenarios	Biscay region, Spain, local residents	- % of area devoted to organic farming - No. of species protected - Quality of water bodies - % of native forest area - Type of recreational activities permitted - Monetary: income tax increase	No
Cerda et al., 2013 https://doi.org/10.1017/S13557700X12000472	Valuation of existence value of endemic moss	Tourists, Chile	- Probability of seeing wild animals - Access - Probability of extinction of certain species - Biodiversity - Monetary: change in income	Images of endemic moss
Foelske and van Riper, 2020 https://doi.org/10.1016/j.apgeog.2020.102355	Preference for mixed-use landscape (residential, industrial, farming, protected areas)	General public (Minnesota, USA)	- Annual population growth (in the county) - % of protected grassland - Distance to recreation areas - & of land used for agriculture - No. of bisons - Monetary: unemployment rate	No images, but pictograms used to help respondents
Grammatikopoulou et al., 2019 https://doi.org/10.1016/j.forpol.2019.04.001	Preference for peatland attributes	General public, Finland	- Change in carbon storage potential - Change in species diversity - Number of lakes with poor water	No

Paper	Objective	Sample	Attributes (relevant to this study)	Images
			- Areas suitable for berry picking - Use of peat for energy production	
Jourdain and Vivithkeyoonvong, 2017 https://doi.org/10.1111/agec.12364	Valuation of ecosystem services by rice agriculture	Residents, a region in Thailand	- Water quality and environment (low quality, for industrial purposes/medium quality, for agricultural purposes/ high quality, for conservation of aquatic animals and safe swimming) - Rural lifestyle and rice landscapes (abandoned land, no agricultural activities, rural lifestyle continues...) - Monetary: voluntary contribution	Yes
Lourenço-Gomes et al., 2020 https://doi.org/10.1016/j.culher.2020.04.018	Preference for rural landscapes in wine producing region	General public, (region in Portugal)	- Terraced vineyards... - Mosaic landscape (vineyards mixed with other crops) - Monetary: Tax	Not in choice cards
Martínez-Jauregui et al., 2019 https://doi.org/10.1016/j.ecoser.2019.100952	Preference for biodiversity indicators in landscapes	General public, Spain	- Genetic variation - Population structure of each species - Number of native species - Number of alien species - Conservation programmes - Monetary: Tax [levels not indicated in paper]	Not in choice cards
Niedermayr et al., 2018 https://doi.org/10.3390/su10062061	Valuation of public good provided by (intensive) agriculture	General public (Marchfeld, Austria)	- Groundwater quality - Landscape quality (Percentage of hedges and flower strips on agricultural land) - Soil functionality in connection with climate stability - Monetary: tax	Yes
Notaro et al., 2019 https://doi.org/10.3390/su14074093	WTP for Alpine landscapes	Tourists, Italy	- Forests: % of different species coverage - Agricultural: Orchards only or mixed crops - Grass land: % of grass, pastures and presence of animals - Monetary: increase in cost of overnight stay	No

Paper	Objective	Sample	Attributes (relevant to this study)	Images
Parron et al., 2022 https://doi.org/10.1016/j.ecoser.2022.101476	Value of ecosystem services amid intensification pressure	General population, Parana State, Brazil	- Visual amenity/appearance of the agricultural landscape - Soil conservation - Carbon storage - Biodiversity, presence and diversity of animals and plants - Monetary: annual cost of the programme per household	Pictograms
Rewitzer et al., 2017 https://doi.org/10.1016/j.ecoser.2017.06.014	Valuation of typical alpine landscapes	Residents, Switzerland	- Number of farms - Area of dry grassland - Area of forest - Protection against natural hazards (number of events within 10 years) - Monetary: tax	Yes, computerised ones
Scarpa et al., 2009 https://doi.org/10.1093/erae/jbp012	Preference for rural landscape	General public, Ireland	- Mountain land - Stonewalls - Farmyard tidiness - Cultural heritage (old farm building and historical heritage) - Monetary: increase in income and value added tax	Yes
Schaak and Musshoff, 2020 https://doi.org/10.1016/j.agsy.2018.06.015	Preference for pasture landscapes	General population, Germany	- Presence of livestock - Number of land parcels - Point landscape elements - Linear landscape elements - Monetary: cost per households per year	Yes
Shr et al., 2019 https://doi.org/10.1016/j.ecolecon.2018.10.015	Valuation of landscape attributes (greenspace around residential areas)	General public (region in England)	- Diversity in plant species - Presence of Water - % of mowed area - Plantation patterns - Monetary: cost of the piece of land	Yes
Tagliafierro et al., 2016 https://doi.org/10.1016/j.ecolecon.2016.03.022	Preference for landscapes	Residents, Sorrento Peninsula, Italy	This is a Contingent Valuation Study (CVM), where they consider: *Complexity* as defined by: - Number of patches - SHEI index	Yes, surface and satellite ones to explain main

Paper	Objective	Sample	Attributes (relevant to this study)	Images
			Visual scale: - Total area of the view - % of open land *Naturalness*: - % of woods or other natural areas *Degree of urbanisation*: - Surface of urban area - Aggregation index *Encumbrance*: - Presence of disturbing elements in the view *Historicity*: - Presence of heritage elements - Presence of traditional lemon orchards *Stewardship*: - Presences of farmers stewardships	scenarios of CVM
Torquati et al., 2020 https://doi.org/10.3390/land9100393	Impact of landscape on residential choices in peri-urban areas	General public (Umbria, Italy)	- Distance to workplace and amenities - Type of landscape: mostly natural, mostly agricultural, mostly industrial, mostly commercial - Monetary: house and land prices	Yes
van Zanten et al., 2016 https://doi.org/10.1016/j.ecolecon.2016.07.008	Preference for landscape	Tourists, Dutch municipality	- Presence of livestock - Maize grassland ratio - Prevalence of hedgerows and tree lines - Prevalence of forest patches - Monetary: Extra costs per overnight stay	Yes

Table A2. Socio-demographic characteristics of Flemish, Hungarian and UK sample.

	Flanders (1)		Hungary (2)		United Kingdom (3)		Sample differences		
Characteristic	**Sample**	**Population**	**Sample**	**Population**	**Sample**	**Population**	**1-2**	**1-3**	**2-3**
Size (n)	345	6,653,062[A]	169	9,750,149[B]	322	67,081,200[C]			
Gender (%)									
Female	52.46	50.84[D]	42.60	52.40[B]	49.07	50.60[B]			
Other	0.87	n.d.	0.00	n.d.	0.70	n.d.			
Mean age (min, max)	50.19 (18, 85)	41.90	45.81 (18, 76)	43.30[D]	53.19 (18, 89)	40.40	**	*	*
Age (%)									
18-34 years	23.77	17.96[A]	22.49	18.43[E]	14.60	25.27[E]		**	
35-54 years	37.68	26.00	49.70	29.73	33.54	26.58	**		***
55 years and over	38.55	35.07	27.81	32.38	51.86	31.46		***	***
Education (%)									
Low (secondary degree or lower)	33.04	15.90[F]	35.51	26.50[G]	45.03	18.30[H]		**	
Medium (bachelor degree)	14.20	38.70	25.44	33.40	17.70	49.40	**		
High (master's degree or higher)	52.75	45.40	39.05[#]	21.80	32.61	27.00	**	***	
Net household income (%)									
Below average	13.91	n.d.	37.27	n.d.	26.04	n.d.	**	***	*
Around average	13.62	n.d.	23.08	n.d.	12.73	n.d.	**	**	
Above average	47.25	n.d.	40.24	n.d.	40.06	n.d.			
Flanders									
Less than 999€/month	1.45	n.d.	.	.	.	.			
1000-1999€/month	12.47	n.d.	.	.	.	.			
2000-3999€/month	42.90	n.d.	.	.	.	.			
More than 4000€/month	17.97	n.d.	.	.	.	.			
Hungary									
Less than 1,199,000 Ft/year	.	.	13.69	n.d.	.	.			
1,200,000-4,799,000 Ft/year	.	.	45.23	n.d.	.	.			
4,800,000-8,399,000 Ft/year	.	.	27.38	n.d.	.	.			

	Flanders (1)		Hungary (2)		United Kingdom (3)		Sample differences		
Characteristic	**Sample**	**Population**	**Sample**	**Population**	**Sample**	**Population**	**1-2**	**1-3**	**2-3**
More than 8,400,000 Ft/year	.	.	3.58	n.d.	.	.			
UK									
Less than 5,000£/year	.	.	.	.	3.73	n.d.			
5000-19,999£/year	.	.	.	.	25.16	n.d.			
20,000-44,999£/year	.	.	.	.	36.02	n.d.			
45,000-99,999£/year	.	.	.	.	24.54	n.d.			
More than 100,000£/year	.	.	.	.	4.35	n.d.			
Don’t know/ no answer	25.22	n.d.	10.12	n.d.	6.21	n.d.			
Mean household size [min, max]	2.50 [1,7]	2.45[F]	2.54 [1,6]	2.30[D]	2.41 [1,7]	2.40[I]			
Province (%)									
Belgium									
Flemish Brabant	15.95	17,47[A]	.	.	.	.			
Limburg	10.72	13,23	.	.	.	.			
Antwerp	30.72	28,19	.	.	.	.			
East-Flanders	26.96	23,02	.	.	.	.			
West-Flanders	15.65	18,09	.	.	.	.			
Hungary									
Southern Great Plain	.	.	8.33	12,63[J]	.	.			
Southern Transdanubia	.	.	5.95	8,97	.	.			
Central Transdanubia	.	.	11.31	10,88	.	.			
Central Hungary	.	.	36.90	31,25	.	.			
Western Transdanubia	.	.	10.12	10,20	.	.			
Northern Great Plain	.	.	12.50	14,80	.	.			
North Hungary	.	.	14.88	11,47	.	.			
UK		.	.	.					
East Midlands	.	.	.	.	6.52	7,25[D]			
East of England	.	.	.	.	10.87	9,35			
Greater London	.	.	.	.	11.18	13,42			
North East	.	.	.	.	4.35	4,00			
North West	.	.	.	.	10.56	10,98			

	Flanders (1)		Hungary (2)		United Kingdom (3)		Sample differences		
Characteristic	Sample	Population	Sample	Population	Sample	Population	1-2	1-3	2-3
Northern Ireland	.	.	.	.	0.93	2,83			
Scotland	.	.	.	.	5.59	0,81			
South East	.	.	.	.	16.46	13,74			
South West	.	.	.	.	9.01	8,44			
Wales	.	.	.	.	6.21	4,72			
West Midlands	.	.	.	.	10.56	8,89			
Yorkshire and the Humber	.	.	.	.	7.76	8,24			
Living environment (%)									
Urban (city or town)	21.74	98.00[B]	67.46	72.00[B]	39.75	82.90[I]	***	***	***
Peri-urban	28.99	n.d.	19.53	n.d.	35.71	n.d.			***
Rural	48.12	2.00	13.02	28.00	23.92	17.10	***	***	*
Don't know/no answer	1.16	n.d.	0.00	n.d.	0.62	n.d.			
Connection to agricultural landscapes (%)									
Personally (or direct relations) work/have worked in the agricultural sector	6.09	n.d.	14.20	n.d.	5.59	n.d.	**		**
Live/have lived in a rural area	30.72	n.d.	37.28	n.d.	17.39	n.d.		***	***
Frequently visit rural areas for leisure activities	17.10	n.d.	31.36	n.d.	18.63	n.d.	***		**

Note: All population statistics are reported for the year 2020 unless otherwise specified.
Note: Significance is indicated with * p<0.05, **p<0.01, or ***p<0.001.
[A] Source: https://statbel.fgov.be/nl (calculated for total population, including 18 years and below).
[B] Source: https://www.worldbank.org/en/home (calculated for total population of Belgium, Hungary and the UK, including 18 years and below).
[C] Source: https://www.ons.gov.uk/ (calculated for total population, including 18 years and below).
[D] Source: https://www.statista.com/ (calculated for total population, including 18 years and below).
[E] Source: https://www.populationpyramid.net/hungary/2019/ (calculated fir total population, for the year 2019).
[F] Source: https://www.vlaanderen.be/statistiek-vlaanderen (calculated for total population, aged between 25-64 years old).
[G] Source: https://www.ksh.hu/interaktiv/storytelling/iskolazottsag/index.html?lang=en (calculated for total population, 15 years old and over, for the year 2016).
[H] Source: https://www.oecd.org/ (calculated for total population, aged between 25-64 years old).
[I] Source: https://www.ons.gov.uk/ (calculated for total population, including 18 years and below).
[J] Source: https://ec.europa.eu/eurostat/en/ (calculated for total population, including 18 years and below).

Table A3. Attitudinal characteristics of the Flemish, Hungarian and UK samples.

Characteristic	Flanders (1)	Hungary (2)	United Kingdom (3)	Sample differences 1-2	1-3	2-3
Environmental attitude						
Pro-environmental membership (%)						
Environmental organisation	8.41	3.55	5.59			
Conservation organisation	7.54	1.18	9.32			
Both environmental and conservation organisation	2.90	2.37	5.90			
NEP scale (mean, SD)[A]	3.60 (0.55)	3.80 (0.56)	3.69 (0.60)	*		
Ecological agriculture attitude						
Effectiveness of agricultural at achieving sustainability goals (mean, SD)[B]	3.60 (0.65)	3.61 (0.77)	3.76 (0.74)		**	
Relationship with nature						
Frequency of outdoor activities (mean, SD)						
Gardening	2.72 (1.38)	2.85 (1.45)	2.81 (1.29)			
Exercise	2.22 (0.50)	1.86 (0.58)	1.76 (0.69)	***	***	
Observational	1.70 (0.84)	2.09 (0.93)	1.74 (1.00)	***		***
Camping	2.30 (1.37)	2.57 (1.47)	2.31 (1.37)			
Restaurant	1.07 (0.44)	1.13 (0.67)	1.09 (0.48)		**	
Importance of local rural landscapes (mean, SD)[C]	3.95 (0.56)	4.04 (0.55)	4.00 (0.51)			
Importance of rural landscape characteristics[D]						
Sense of order and care	3.59 (1.04)	4.21 (0.91)	3.77 (0.98)	***	*	***
Balanced landscape (coherence between usages)	3.74 (0.88)	4.27 (0.83)	3.94 (0.89)	***	**	***
Presence of cultural elements	3.60 (0.92)	4.14 (0.87)	3.92 (0.88)	***	***	*
Openness and depth of view	3.82 (0.87)	4.28 (0.72)	4.06 (0.81)	***	***	*
Presence of iconic elements	3.82 (0.89)	4.41 (0.77)	4.10 (0.86)	***	***	***
Wilderness, the idea that what you see is ecologically robust	3.83 (0.83)	4.20 (0.86)	3.98 (0.84)	***		*
Impact of COVID-19 on relationship with nature (%)						
Stayed the same	57.68	66.27	44.10			
Feel stronger link with nature	35.36	24.26	43.17			
Feel weaker link with nature	2.61	8.28	8.39			
Don't know/no answer	4.35	1.18	4.35			

Note: Significance is indicated with * p<0.05, **p<0.01, or ***p<0.001.

[A] The New Environmental Paradigm (NEP) scale is measured on a 5-point Likert scale (1 = completely disagree, 5 = completely agree). Mean scores close to 1 indicate a strong anthropocentric environmental attitude, while scores close to 5 indicate a strong eco-centric attitude.

[B] Effectiveness is measured on a 5-point Likert scale (1 = not effective at all, 5 = very effective). Mean scores close to 1 indicate respondents consider agriculture ineffective at achieving sustainability goals, while scores close to 5 indicate strong effectiveness.

[C] The importance of local rural landscapes is measured on a 5-point Likert scale (1 = completely disagree, 5 = completely agree).

[D] The importance of rural landscape characteristics is measured on a 5-point Likert scale (1 = not important at all, 5 = very important).

Appendix B

Table B1. G-MNL model with Hungary as main effects and Flanders and UK as interactions effects.

	Main effects		Interaction effects	
Attributes	β	**SD**	$\beta_{Flanders}$	β_{UK}
Opt-out	-12.072***	7.809***	-1.327	1.044
Land coverage [None]				
Covered	0.057	0.079	-0.183	0.006
Landscape diversity [Monoculture]				
Low	1.051***	0.488***	0.836**	-0.006
Medium	1.531***	0.211	1.168**	0.174
High	1.796***	0.504*	1.818***	0.829*
Crop dividers [None]				
Wild, unmanaged	0.235	0.101	0.109	0.058
Clear, well-managed	0.564**	0.295**	0.219	0.259
Mechanisation levels [High]				
Medium	-0.592	0.271	-0.719	-0.101
Low	-0.434	0.065	-0.313	0.097
None	-0.296	0.109	-0.544	-0.310
Infrastructure [Large]				
Small	0.065	0.117	-0.655	-0.416
Medium	-0.002	0.201	-0.863*	-0.579
Energy generating infrastructure [Low][A]				
Medium	0.142	0.124	-0.204	-0.002
High	0.343	0.065	-0.216	-0.110
Very high	0.415*	0.622***	0.311	0.077
Price (PPP €)	-0.139***	0.250***	-0.119*	-0.133*
δ **(Hungary)**	-0.324*			
δ **(UK)**	-0.139			
τ	1.020***			
N	22572			
Log-likelihood	-5332,49			
AIC	10798,99			
BIC	11336,63			

Note: Significant coefficients are indicated with * p<0.05, **p<0.01, or ***p<0.001. The reference level of each attribute is indicated in square brackets.

[A] Levels for the attribute *Energy generating infrastructure* have been coded as *Low* (solar panels on roofs), *Medium* (Solar panels on roofs and ground), *High* (Solar panels on roofs and ground + wind turbines <25m high), and *Very high* (Solar panels on roofs and ground + wind turbines >25m high).

Table B2. Estimates (β) and standard deviations (SD) reflecting WTP estimates and heterogeneity of preferences, respectively. Estimates using MXL model in WTP-space for Flanders, Hungary, and the United Kingdom (UK).

	Flanders		Hungary		UK	
Attributes	β	**SD**	β	**SD**	β	**SD**
Opt-out	-69.415****	54.954****	-50.529****	20.454****	-45.151****	31.257****
Land coverage [None]						
Covered	-0.680	0.756	-0.290	0.358	0.448	1.302**
Landscape diversity [Monoculture]						
Low	8.747****	0.287	5.082****	2.972****	5.227****	2.631**
Medium	12.187****	2.513***	6.587***	0.134	7.974****	0.196
High	15.383****	3.868***	9.234****	4.572	10.180****	4.885****
Crop dividers [None]						
Wild	1.292	0.933	0.583	1.683	0.568	0.573
Clear	3.113****	0.116	2.807****	1.082	2.785****	1.550**
Mechanisation [High]						
Medium	-3.128	1.710	-2.308	3.458***	-1.913	1.954**
Low	-1.854	1.208	-2.487*	0.813	-0.930	2.509**
No	-1.341	0.419	-1.331	3.632**	-1.528	3.846****
Infrastructure [Large]						
Small	-1.416	0.706	0.413	0.050	-0.075	0.211
Medium	-3.124**	0.228	-0.213	0.792	-1.249	0.859
Energy generating infrastructure [Low][A]						
Medium	0.097	0.219	1.161	1.318	0.410	0.421
High	-0.147	1.816*	1.895*	0.448	-0.470	0.483
Very high	2.276**	3.684***	2.632**	0.501	1.294	0.903
Price (€)	-2.351****	0.824****	-2.154****	0.963****	-2.111****	0.842****
N	9135		4563		8694	
Log-likelihood	-2187.060		-1108.260		-2201.910	
AIC	4438.116		2280.511		4467.827	
BIC	4666.576		2486.135		4694.080	

Note: Significant coefficients are indicated with * p<0.1, ** p<0.05, *** p<0.01, or **** p<0.001. Reference level of each attribute is indicated in square brackets.

[A] Levels for the attribute *Energy generating infrastructure* have been coded as *Low* (solar panels on roofs), *Medium* (Solar panels on roofs and ground), *High* (Solar panels on roofs and ground + wind turbines <25m high), and *Very high* (Solar panels on roofs and ground + wind turbines >25m high).

Table B3. Decomposition of socio-demographic, attitudinal, and recreational characteristics of respondents between latent classes.

Respondent characteristics	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**1-2**	**1-3**	**1-4**	**2-3**	**2-4**	**3-4**
Size (n)	241	172	355	68						
Study area (%)										
Flanders	37.76	39.53	45.35	36.76						
Hungary	21.58	19.19	21.41	11.76						
UK	40.66	41.28	33.24	51.47						**
Gender (% female)	47.72	52.91	48.45	48.53						
Age (mean, σ)	48.89 (16.64)	50.79 (14.73)	51.75 (15.80)	48.44 (14.73)						
Education (%) *										
Low (secondary degree or lower)	43.15	40.70	34.65	54.41						***
Medium (bachelor degree)	17.84	18.60	17.18	19.12						
High (master's degree or higher)	39.00	40.70	48.17	26.47						***
Net Household income/month (%) ***										
Below average	28.63	26.16	22.25	27.94						
Around average	15.77	14.53	16.06	10.29						
Above average	42.74	39.53	48.45	25.00			*			***
No answer	12.86	19.77	13.24	36.76			***		***	***
Household size (mean, σ)	2.60 (1.30)	2.41 (1.17)	2.45 (1.15)	2.35 (1.00)						
Living environment (%)										
Urban	39.83	37.79	37.46	33.82						
Peri-urban	25.31	32.56	30.14	35.29						
Rural	34.85	28.49	31.83	27.94						
No answer	0.00	1.16	0.56	2.94						
Connection to agricultural landscape (%)										

Respondent characteristics	Class 1	Class 2	Class 3	Class 4	1-2	1-3	1-4	2-3	2-4	3-4
Personally (or direct relations) work/have worked in the agricultural sector	9.54	6.40	7.89	1.47						
Live/have lived in a rural area	27.80	20.93	30.99	17.65				*		
Frequently visit rural areas for leisure activities	18.67	16.86	24.79	14.71						
None	43.98	55.81	36.34	66.18			*	***		***
New Environmental Paradigm (NEP) score (mean, σ)* **	3.59 (0.54)	3.66 (0.59)	3.76 (0.56)	3.49 (0.65)						
Ecological agriculture attitude										
Effectiveness of agricultural at achieving sustainability goals (mean, SD)[B]	3.71 (0.69)	3.65 (1.43)	3.68 (0.72)	3.43 (0.81)			**			*
Relationship with nature										
Frequency of outdoor activities (mean, SD)	2.14 (0.72)	1.93 (0.57)	2.02 (0.54)	1.92 (0.65)	***		*			
Gardening	2.94 (1.36)	2.72 (1.37)	2.76 (1.36)	2.56 (1.33)						
Exercise	2.06 (0.74)	1.87 (0.59)	1.98 (0.56)	1.87 (0.63)	**					
Observational	1.95 (1.04)	1.68 (0.83)	1.75 (0.90)	1.73 (0.94)	**	*				
Camping	2.39 (1.40)	2.23 (1.36)	2.44 (1.42)	2.12 (1.36)						
Restaurant	1.23 (0.78)	1.08 (0.40)	1.05 (0.35)	1.16 (0.66)	**	***				
Importance of local rural landscapes (mean, SD)[C]	3.97 (0.55)	3.88 (0.56)	4.05 (0.48)	3.75 (0.67)			**	***		***

Respondent characteristics	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**1-2**	**1-3**	**1-4**	**2-3**	**2-4**	**3-4**
Importance of rural landscape characteristics										
Sense of order and care	3.83 (0.96)	3.71 (0.96)	3.84 (1.06)	3.56 (1.11)						
Balanced landscape (coherence between usages)	3.94 (0.63)	3.74 (0.93)	4.06 (0.86)	3.62 (1.07)				***		***
Presence of cultural elements	3.90 (0.86)	3.62 (0.94)	3.93 (0.92)	3.62 (0.95)	**			***		*
Openness and depth of view	4.00 (0.83)	3.93 (0.79)	4.09 (0.84)	3.72 (0.94)			*			***
Presence of iconic elements	4.06 (0.85)	3.89 (0.89)	4.16 (0.85)	3.78 (1.03)				***		***
Wilderness, the idea that what you see is ecologically robust	3.90 (0.78)	3.85 (0.92)	4.10 (0.83)	3.74 (0.96)		**		**		***
Impact of COVID-19 on relationship with nature (%)										
Stayed the same	46.89	62.79	54.93	54.41	***					
Feel stronger link with nature	37.76	30.23	38.31	33.82						
Feel weaker link with nature	10.37	2.91	4.23	7.35	***	**				
Don’t know/no answer	4.97	4.07	2.54	4.41						

Note: Significant coefficients are indicated with *p<0.10, **p<0.05, ***p<0.01.

Table B4. G-MNL model with interaction effect for education level. Low education level (secondary of lower) as main effects, and interaction effects for medium (bachelor or equivalent) and high (master or higher) education levels.

	Main effects		Interaction effects	
Attributes	β	**SD**	β_{medium}	β_{high}
Opt-out	-8.128***	5.181***	-0.364	-1.897**
Land coverage [None]				
Covered	-0.001	0.042	0.259	-0.042
Landscape diversity [Monoculture]				
Low	0.931***	0.283	0.165	0.692**
Medium	1.514***	0.135	0.174	0.547*
High	1.993***	0.622***	0.378	0.931***
Crop dividers [None]				
Wild, unmanaged	0.218**	0.040	0.067	0.145
Clear, well-managed	0.571***	0.195**	-0.287	0.031
Mechanisation levels [High]				
Medium	-0.451*	0.425*	0.413	-0.978*
Low	-0.328*	0.288**	0.251	-0.280
None	-0.396**	0.116	-0.422	-0.113
Infrastructure [Large]				
Small	-0.102	0.128	0.348	-0.579*
Medium	-0.223	0.058	0.018	-0.555
Energy generating infrastructure [Low][A]				
Medium	0.049	0.084	-0.030	-0.094
High	0.121	0.148	-0.399	0.158
Very high	0.405***	0.646***	-0.274	0.198
Price (PPP €)	-0.180***	0.211***	0.064	-0.048
δ **(Hungary)**	0.050			
δ **(UK)**	0.087			
τ	0.934***			
N	22,572			
Log-likelihood	-5335.8933			

Note: Significant coefficients are indicated with * p<0.05, **p<0.01, or ***p<0.001. The reference level of each attribute is indicated in square brackets.

[A] Levels for the attribute *Energy generating infrastructure* have been coded as *Low* (solar panels on roofs), *Medium* (Solar panels on roofs and ground), *High* (Solar panels on roofs and ground + wind turbines <25m high), and *Very high* (Solar panels on roofs and ground + wind turbines >25m high).

Table B5. G-MNL model with interaction effect for household income level. Equal to national average income level as main effects, and interaction effects for below and above average national income levels.

	Main effects		Interaction effects	
Attributes	β	**SD**	$\beta_{below\ average}$	$\beta_{above\ average}$
Opt-out	-9.575***	5.471***	0.906	0.836
Land coverage [None]				
Covered	-0.051	0.111	-0.003	0.127
Landscape diversity [Monoculture]				
Low	1.123***	0.377**	-0.554**	0.351
Medium	1.455***	0.199	-0.167	0.744**
High	2.400***	0.609***	-0.515*	0.133
Crop dividers [None]				
Wild, unmanaged	0.303*	0.020	0.060	-0.108
Clear, well-managed	0.620***	0.307***	0.010	-0.075
Mechanisation levels [High]				
Medium	-1.186**	0.578***	0.688	0.783
Low	-0.923***	0.050	0.786*	0.806*
None	-0.435	0.171	0.025	-0.042
Infrastructure [Large]				
Small	-0.592**	0.042	0.408	0.605*
Medium	-0.484	0.103	0.029	0.256
Energy generating infrastructure [Low][A]				
Medium	0.168	0.020	0.021	-0.256
High	0.358	0.100	-0.080	-0.440
Very high	0.552**	0.713***	-0.193	-0.165
Price (PPP €)	-0.219***	0.216***	0.030	0.013
δ **(Hungary)**	-0.090			
δ **(UK)**	0.041			
τ	0.945			
N	22,572			
Log-likelihood	-5342.2489			

Note: Significant coefficients are indicated with * p<0.05, **p<0.01, or ***p<0.001. The reference level of each attribute is indicated in square brackets.

[A] Levels for the attribute *Energy generating infrastructure* have been coded as *Low* (solar panels on roofs), *Medium* (Solar panels on roofs and ground), *High* (Solar panels on roofs and ground + wind turbines <25m high), and *Very high* (Solar panels on roofs and ground + wind turbines >25m high).

Table B6. G-MNL model with interaction effect NEP-score. Ecocentric attitudes (NEP-score > 3) as main effects and anthropocentric attitudes (NEP-score <= 3) as interaction effect.

	Main effects		Interaction effect
Attributes	β	SD	$\beta_{below\ average}$
Opt-out	-9.575***	5.471***	0.906
Land coverage [None]			
Covered	-0.051	0.111	-0.003
Landscape diversity [Monoculture]			
Low	1.123***	0.377**	-0.554**
Medium	1.455***	0.199	-0.167
High	2.400***	0.609***	-0.515*
Crop dividers [None]			
Wild, unmanaged	0.303*	0.020	0.060
Clear, well-managed	0.620***	0.307***	0.010
Mechanisation levels [High]			
Medium	-1.186**	0.578***	0.786*
Low	-0.923***	0.050	0.688
None	-0.435	0.171	0.025
Infrastructure [Large]			
Small	-0.592**	0.042	0.408
Medium	-0.484*	0.103	0.029
Energy generating infrastructure [Low][A]			
Medium	0.168	0.020	0.021
High	0.358	0.100	-0.080
Very high	0.552**	0.713***	-0.193
Price (PPP €)	-0.219***	0.216***	0.030
δ **(Hungary)**	-0.090		
δ **(UK)**	0.041		
τ	0.945***		
N	22,572		
Log-likelihood	-5342.072		