Local support for agri-environmental measures and the role of knowledge and environmental attitudes

by Lysander Fockaert, Erik Mathijs, and Liesbet Vranken

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Abstract

Local residents are important stakeholders in rural social-ecological systems. They are beneficiaries of the public goods and services provided by agri-environmental measures (AEM) and contribute to the public money used in the CAP to compensate the farmers. They also interact with farmers on a day-to-day basis, exerting pressure for more sustainable agriculture or expressing support and appreciation for ongoing efforts. However, little is known on public preferences for specific AEM and determinants of these opinions. A discrete choice experiment was distributed to a panel of citizens in a rural area in Flanders. Hybrid choice modeling indicated support for each AEM, although with substantial heterogeneity. Mechanical weeding and nesting opportunities for bees and birds were particularly favored, whereas grass strips, pheromone treatments against pests and hedgerows with low management regimes received less support. A pro-environmental attitude only influenced preferences for a few specific practices. Illusory knowledge, but not actual knowledge, was strongly correlated to this environmental attitude. This indicates that rational factors and environmental concerns play only a limited role and other considerations (e.g. health, aesthetics or social aspects), biases, ignorance and misconceptions are more salient in the societal debate on greening of agriculture. Increasing public awareness can justify the high demand for AEM, while strengthening farmer-citizen relationships might allow expression of public acknowledgement, thereby enhancing farmer participation in such schemes.

1. **Introduction**

Agricultural intensification results in a landscape with decreasing species numbers, population sizes and environmental quality (Dupas *et al.*, 2015; Green *et al.*, 2005; Kleijn *et al.*, 2009; Kopittke *et al.*, 2019). Since agriculture takes up a large proportion of the European landscape, society demands farmers to increase efforts for adequate and sustainable management of the agro-ecosystem (Hall *et al.*, 2004; TNS opinion & social, 2016). Although discussion about the optimal strategy to increase ecological quality in rural areas is ongoing (Green *et al.*, 2005; Kremen, 2015; Kremen and Miles, 2012; Phalan *et al.*, 2011; Phalan, 2018), it is believed that agri-environmental schemes and measures (AES/AEM) can contribute to (local) conservation of biodiversity (Batáry *et al.*, 2015; Kleijn *et al.*, 2006; Merckx *et al.*, 2009; Pfiffner *et al.*, 2019) and provision of ecosystem services (ESS) that contribute to society's wellbeing (Delbaere *et al*., 2014; Sutter *et al*., 2018; Cahenzli *et al*., 2019; Albrecht *et al*., 2020). Several types of AEM exist, e.g. on-field practices to lower inputs or setting aside land on parcel boundaries for hedgerows or vegetation strips. Some measures require relatively low effort, such as the provision of nesting places for birds and bees, others demand acquisition of specialized material and machinery.

Society's awareness of and willingness-to-pay for regional public goods have been identified as important preconditions for farmers' adoption of AEM (Gatto *et al*., 2019; Targetti *et al*., 2019). AEM can increase bridging social capital for farmers, through recognition and appreciation of a farmer's contributions to society (de Krom, 2017; Matzdorf and Lorenz, 2010). Bridging social capital can increase trust in the community and support collective action for the management of public goods (Arnott *et al.*, 2021). In recent reports on the motivation of Flemish farmers to cooperate in AEM, farmers indicated that the practices can contribute to market opportunities and a positive reputation of their farm. Information transfer to the general population about their efforts was appreciated, although the farmers acknowledged that information boards did not result in increased awareness in society, which was conceived to be rather limited (de Regt *et al*., 2018; Ghyselinck, 2020). Public opinion also has an influence on policy-making itself, as shown by the strong emphasis on environmental issues in the European CAP (Baldock *et al*., 2002). When those policies are too restrictive or limit the autonomy of the farmers, they can perceive large pressures and there is a potential risk that the farmer reverts to a defensive attitude, hampering collaboration and societal engagement (Siebert *et al*., 2006). It might therefore be relevant to study public considerations on the implementation of existing measures, both from the standpoint of farmers' participation as for the evaluation of current policies. However, assessments of public attitudes towards specific management interventions are rare (Tindale *et al.*, 2020, preprint).

Most efforts on public valuation of rural environments are aimed at local demand for ecosystem services or (outcomes of) broad-scale landscape interventions (Foster and Mourato, 2000; Colombo *et al*., 2005; Scarpa *et al*., 2007; Colombo *et al*., 2009; Dachary-Bernard and Rambonilaza, 2012; Bernués *et al.*, 2014, 2019; Tienhaara *et al.*, 2020). In these studies, the role of the farmer is often minimized and the methods to achieve higher provision of the ESS are of lesser importance (Hall *et al.*, 2004; Vainio *et al.*, 2021) or framed as policy interventions (Colombo *et al*., 2009; Dachary-Bernard and Rambonilaza, 2012). Other studies focus specifically on the aesthetic impact of rural interventions (Arnberger and Eder, 2011; Boeraeve *et al.*, 2020; Dupras *et al*., 2018; van Zanten *et al*., 2016). Although the findings in these studies are interesting for policy-design and landscape planning, they provide little information on public recognition of practices applied by the farmers. The provision of rural public goods does not necessarily require interventions in agricultural management, but the public seems to consider farmers as primary providers of such goods (Hellerstein *et al.*, 2002; Hall *et al*., 2004). It would therefore be relevant for future studies to clearly delineate the role of the farmer when eliciting public preferences for such amenities.

Preferences for AEM and agricultural landscape configurations were found to be influenced by cognitive factors, such as environmental awareness (López-Santiago *et al.*, 2014), environmental attitude (Faccioli *et al.*, 2020; Vera-Toscano *et al.*, 2008) and general beliefs on the need for environmental action (Sauer and Fischer, 2010). Sauer and Fischer suggest that studies on public preferences should take attitudes and other cognitive aspects into account, rather than WTP. Hybrid choice modeling (HCM) integrates structural equation models (SEM) in choice modelling, allowing for inclusion of latent cognitive variables (Ben-Akiva *et al.*, 2002a, 2002b). This is expected to give more accurate results, compared to a sequential approach (Choi and Fielding, 2013) or using composite scores (Schulz *et al*., 2014; Sangkapitux *et al.*, 2017) that are prone to measurement errors (Ben-Akiva *et al.*, 2002b). HCM are particularly useful to study the cognitive process of decision-making and when the observed variables only have indirect effects on the choice itself (Vij and Walker, 2016). Although these models have been used for many years in other scientific fields, they are only recently applied to environmental research (Kim *et al*., 2014; Hoyos *et al.*, 2015; Taye *et al*., 2018; Faccioli *et al.*, 2020).

In this study, the role of environmental attitude in the preference and appreciation for AEM is assessed by means of HCM. Milfont and Duckitt (2010) developed the Environmental Attitude Inventory (EAI) with 12 attitude scales based on preceding literature. Each of these scales covers a specific aspect of environmental attitude, such as enjoyment of nature, support for interventionist policies or the attitude towards altering of nature to fulfill human needs. Preservation, an ecocentric dimension focusing on the conservation of nature, and Utilization, an anthropocentric dimension with a focus on the utilization of nature, are seen as higher-order dimensions of these attitudes

(Milfont and Duckitt, 2010). The two dimensions are considered to be of an orthogonal and complementary nature (Wiseman and Bogner, 2003). However, high (negative) correlations between the scores on Preservation and Utilization have been observed (Milfont and Duckitt, 2010; Milfont *et al*., 2010; O'Callaghan *et al.*, 2012) and Milfont and Duckitt (2010) therefore suggest that both a two-factor and single-factor model should be tested.

Gifford and Nilsson (2014) identified both self-reported/stated/perceived/subjective knowledge and correct/objective/actual knowledge, among many others, as important predictors of pro-environmental behavior. The mediating role of attitude in this relationship has been studied for many decades. Arcury (1990) found significant, although moderate correlations between several types of knowledge and environmental attitude. Bamberg and Möser (2007) identified knowledge and awareness of environmental problems as important, but indirect determinants of pro-environmental behavior, with mediation by several latent cognitive variables. However, in that meta-analysis different specifications of knowledge, objective and subjective, were pooled into the construct "problem awareness", further complicating the interpretation of the observed effects (Bamberg and Möser, 2007; Geiger *et al*., 2019). Yang *et al*. (2020) differentiate between actual and illusory knowledge on the issue of climate change, decoupling objective and subjective knowledge. Although environmental policies often aim to steer stakeholder decision-making through objective information transfer, individuals may rather base their attitudes and preferences, i.e. subjective judgements, on the knowledge they perceive to possess and to be true. Given that stakeholders' knowledge of relevant concepts can increase perception and understanding of the effects of agricultural management interventions (Lamarque *et al.*, 2011), it is assumed to be useful to further investigate the relationship between objective and subjective knowledge measures, environmental attitudes and preferences for AEM.

2. **Material and methods**

2.1 Study area

The study area covers the 41 municipalities of the rural regions of Hageland and the Flemish part of Hesbaye, located in the south-east of Flanders, Belgium (Figure 1A). The size of the study area is 1,900 km^2 (Informatie Vlaanderen, 2018), with a total population of 739,450 inhabitants (in 2020). Population density for the study area is rather low, with on average 389 inhabitants/km^2, whereas the Flemish average is 487 inhabitants/km^2 (STATBEL, 2021a). The study region is mostly dominated by agriculture (47.16%) (Figure 1B). There is a significant specialization in perennial fruit production, with apple and pear orchards on the loamy slopes, mostly in the central part of the study region (6% of the total area, 13% of the total utilized agricultural area (STATBEL, 2021b)) (Figure 1D) (GDI-Vlaanderen, 2019). Although arable farming takes up more land than fruit farming, especially in the Dry Hesbaye region in the south (Figure 1B), the aesthetically appealing orchards are a dominant feature of the landscape and very characteristic to this part of Flanders. They are also important for the touristic sector, as they attract many visitors during the flowering season (Toerisme Vlaanderen, 2021). Specific environmental challenges in the region are erosion, flooding and low water quality partly due to the use of pesticides. Ecologically valuable ecosystems are sparse and small (Figure 1C) (Reynders *et al.*, 2012).

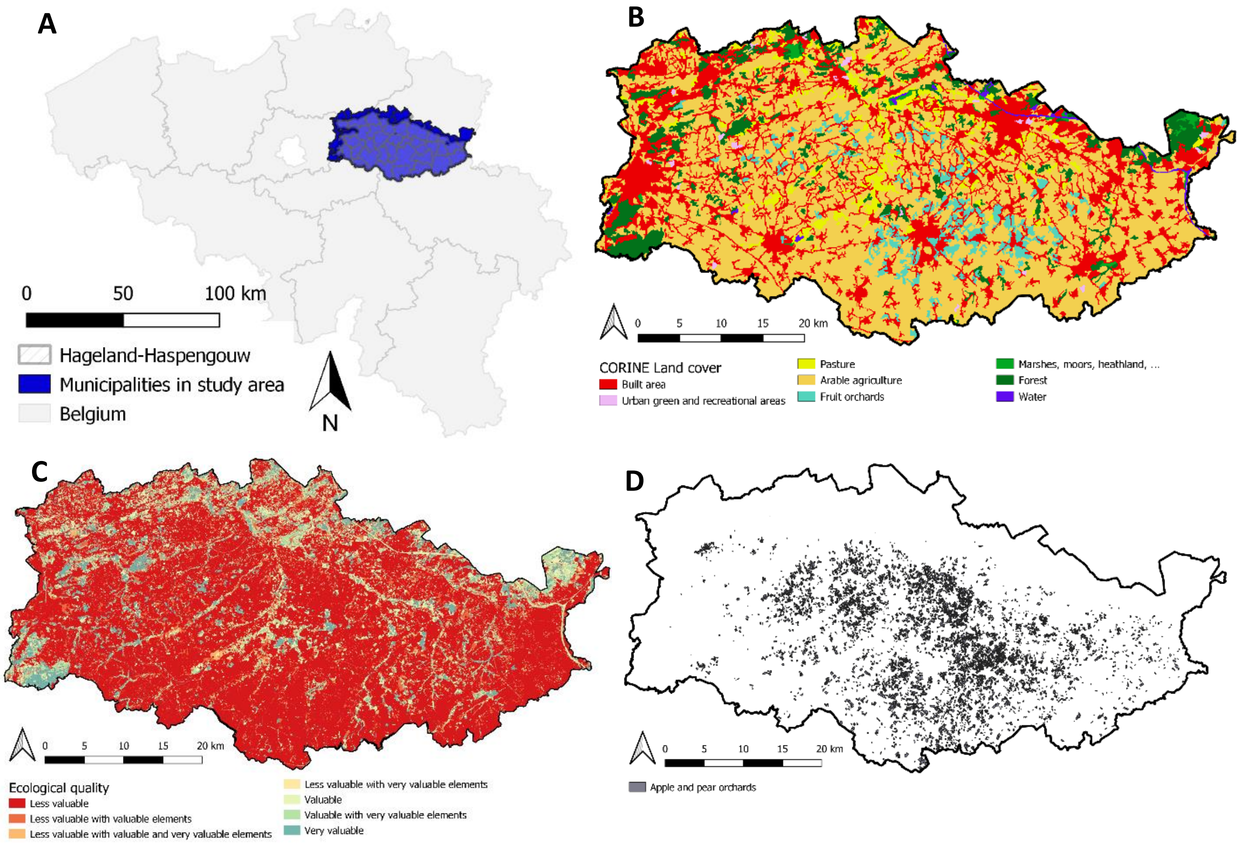

Figure 1 A. Situation of the study area in Belgium. The study area comprises all Flemish municipalities within or overlapping with the Hageland and Haspengouw/Hesbaye regions. B. Simplified CORINE land cover map of the study area in 2018. The area is mostly covered by urban fabric, non-irrigated arable land, pastures and orchards (European Environment Agency, 2020). C. Ecological quality of the study area in 2020. D. Location of apple and pear orchards in the study area in 2018 (GDI-Vlaanderen, 2019)

2.2 Experimental and survey design and sampling

A questionnaire with a discrete choice experiment (DCE) was distributed to a panel of citizens living in the study area. In the DCE a randomly selected block of 6 choice cards in randomized order, out of 4 blocks with 24 choice cards in total, was shown to each respondent. For each choice card, respondents had to select the most preferred option from 3 scenarios, one of them being a baseline scenario, i.e. a conventional orchard without any nature-friendly practices, and 2 orchards where a unique set of AEM's is applied (Figure 2A). A D-optimal MNL design (D-error = 0.214) was generated in Ngene v.1.2.1 (ChoiceMetrics, Sydney). The scenarios are described by 6 attributes (Figure 2B): field margins (3 levels: grass strips, flower strips and absence), wooden linear landscape elements (4 levels: hedgerows with high management, hedgerows with low management, wooded margins and absence), weed management (2 levels: mechanical weeding and spraying of herbicides), mating disruption of coddle moth (2 levels: implementation and absence), voluntary creation of nesting accommodation (4 levels: for bees, for birds, for mammals and none) and a monetary attribute (4 levels: €15, €30, €45 and €60). Attribute and level selection was based on a literature review, expert consultation and interviews with farmers and governmental coordinators. Although it is rarely the case, these practices could be implemented in and around a single orchard. Dummy-coding was applied, with absence of the practice as the reference (herbicide spraying in case of the weed management attribute). In the baseline scenario (SQ), all attributes had the reference level and €0 for the monetary attribute. Only when the respondent chose the SQ option in each of the 6 choice cards, a supplementary question inquired for the respondent's motivation.

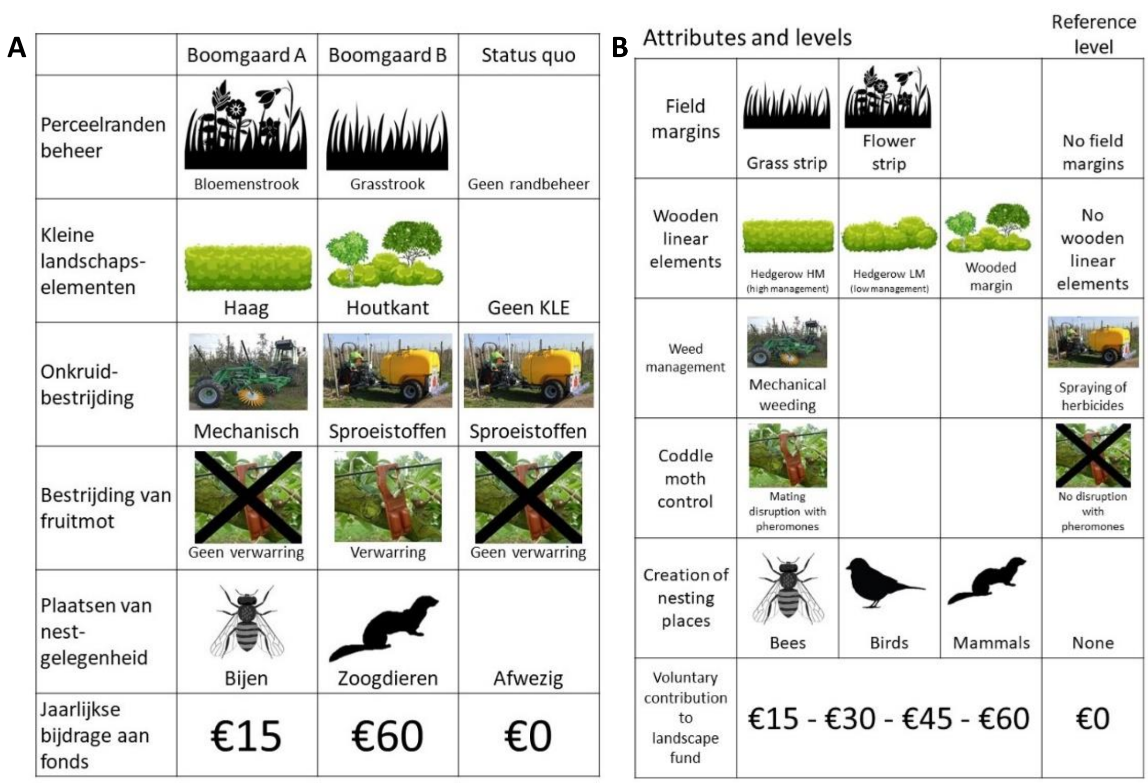

Figure 2 A. Example of a choice card with two scenarios for an orchard (Boomgaard A and B) and a SQ option without any AEM. B. Attributes and levels used in the discrete choice experiment.

The questionnaire started with a short introduction and a form of informed consent, followed by a section on socio-demographic variables. Environmental attitudes were measured through 7-point Likert scale items, taken from the thematic scales of the shortened and optimized Environmental Attitude Inventory (EAI) (Sutton and Gyuris, 2015) i.e. 9 indicators for the Preservation dimension (items of the scales on support for interventionist policies, eco-centric concern and environmental fragility) and 10 items for the Utilization dimension (from the altering nature, anthropocentric concern and human utilization scales). This part was followed by an explanation of the AEMs included in the choice experiment. Next, the respondents were asked to state the amount of knowledge they assumed to have on 10 themes relating to sustainable agriculture in Flanders on a scale from 0 ("*I know nothing about this*") to 10 ("*I know everything about this*") to measure perceived knowledge, similar to the study of Yang *et al*. (2020). This was followed by the DCE. The last part of the questionnaire was a series of 12 True/False questions (including the option "*I don't know*") related to the AEMs of the DCE. Correct answers were added to a total score on 12, which was only presented to the respondent if they were interested in this score, possibly accompanied by an overview of the correct answers and/or additional background information.

Sampling was performed by a marketing agency that distributed the survey link to a panel of eligible respondents living in the study area. Representativeness of the sample was controlled as much as possible by accounting for age, gender and education level. However, to enable inclusion of observations across the entire area, some categories of respondents are overrepresented because of a limited number of potential respondents in the lesser populated, rural municipalities.

The survey, study design and sampling strategy were assessed on privacy and ethics and subsequently approved by the social and societal ethics committee of the KU Leuven.

2.3 Data cleaning and analysis

The sample included 428 responses, but 35 observations were removed due to incomplete data or non-eligible responses, resulting in a final sample size of 393 respondents with 2,358 choice observations (6 choice cards/respondent).

The perceived knowledge score was calculated as the average of the self-reported subjective knowledge scores on five relevant themes, rescaled to a score between 0 and 1. These five subthemes were found to be most indicative of subjective knowledge on the issue of AEM, i.e. environmental impact of conventional agriculture in Flanders, implementation of nature-friendly agricultural practices, environmental impact of nature-friendly agricultural practices, state of biodiversity in rural Flanders and state of ESS in rural Flanders. The actual knowledge score, i.e. the score on the 12 True/False questions was rescaled to 0 and 1 as well. Illusory knowledge was subsequently calculated as the difference between perceived and actual knowledge, with a possible range between -1 and 1.

The HCM analysis was preceded by confirmatory factor analysis (CFA) using the *lavaan* package in R (Rosseel *et al.*, 2019). The EAI-items were implemented in the CFA as indicators in the measurement models of individual scales, a 2-factor model and a single GEA model. Latent variables based on the 6 individual scales resulted in a non-positive definite covariance matrix, indicating poor model specification. The three items of the anthropocentric concern scale were excluded from all further analyses due to ambiguous results. Although model fit for the 2-factor model with a Preservation and a Utilization LV was adequate (CFI: 0.90, TLI: 0.87, RMSEA: 0.06, SRMR: 0.06), a very large negative covariance between the LV's was observed (-0.91), indicating poor discriminant validity (Brown, 2006). A model with a single LV (GEA) resulted in a slightly worse model fit (differences of fit indices with 2-factor model <0.01), but without any problematic cases in the loadings or other parameters. Thus, only the HCM with a single GEA LV will be presented here.

2.2 Choice models

DCE's are based on the Random Utility Maximization model (RUM), proposed by McFadden (1974), which states that the utility (*U*) provided by a good (or a policy scenario) (i) to an individual (*n*) can be described by a random (ε_{ni}) and a non-random part (V_{ni}). A second assumption of the model is that when there is a set J of multiple goods available, an individual will choose the good i ($y_{ni} = 1$) that maximizes their utility. Additionally, the Characteristics Theory of Value (Lancaster, 1966) states that utility obtained from a good is derived from its characteristics, so that (the observed part of) utility can be described as a linear function of the observed characteristics (or attributes) of the good or scenario ($\boldsymbol{x_{ni}}$) and a vector of coefficients ($\boldsymbol{\beta}$). These three assumptions are given by the following equations:

$$y_{ni} = 1 \; if \; U_{ni} > U_{nj} \; \forall \; j \neq i \in J$$

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \; \boldsymbol{\beta x_{ni}} + \; \varepsilon_{ni}$$

With these theories in mind, it is possible to describe the probability (P_{ni}) of individual *n* choosing alternative i from a set of goods J as follows (Train, 2009):

$$P_{ni} = Prob\left(U_{ni} > \; U_{nj} \; \forall \; j \; \neq i\right)$$

$$P_{ni} = Prob\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \; \forall \; j \; \neq i\right)$$

$$P_{ni} = Prob\left(V_{ni} - V_{nj} > \varepsilon_{nj} - \varepsilon_{ni} \; \forall \; j \; \neq i\right)$$

$$P_{ni} = \int_{\varepsilon} \; I(V_{ni} - V_{nj} > \varepsilon_{nj} - \varepsilon_{ni}) \; \forall \; j \; \neq i) f(\varepsilon_n) d\varepsilon_n$$

The indicator function $I(\cdot)$ returns 1 if the condition is true and 0 otherwise. By assuming an i.i.d. extreme value distribution for ε_n, the integral can be approached by a logit function, which only requires the observed part of utility. Assuming that utility is linear in parameters, this can be written as follows:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} = \frac{e^{\boldsymbol{\beta x_{ni}}}}{\sum_j e^{\boldsymbol{\beta x_{nj}}}}$$

If $\boldsymbol{x_{ni}}$ is only a vector of characteristics of the alternative, this is called the conditional logit (CL) model. If the vector contains characteristics of the individual making the choice, it is a multinomial (MNL) logit model (Hoffman and Duncan, 1988), although these terms are often used interchangeably.

The CL model is restricted by a set of assumptions, which are rarely true in reality. One of these assumptions is homogeneity in taste in the population, i.e. the vector $\boldsymbol{\beta}$ is the same for each individual. This is often not the case, especially concerning goods and policy scenarios that are recurring subjects of debate in society. Heterogeneity can be accounted for by defining a continuous distribution for the relevant parameters (e.g. mixed multinomial logit models, MMNL). In MMNL models, every individual has a unique set of parameters ($\boldsymbol{\beta'}$), which are assumed to randomly vary in the population, following a specified distribution, e.g. the normal distribution with a mean μ and standard deviation σ, which results in the following model specification for the mixed logit probability P_{ni}:

$$\beta' \sim N(\mu, \sigma^2)$$

$$P_{ni} = \int \left(\frac{e^{\boldsymbol{\beta' x_{ni}}}}{\sum_j e^{\boldsymbol{\beta' x_{nj}}}} \right) f(\beta) d\beta$$

An additional feature of discrete choice models is the possibility to estimate willingness-to-pay (WTP) values for each attribute, when a price attribute is included in the choice experiment. This WTP is determined by taking the negative ratio of the respective parameters after estimation in preference space or by estimating the model in WTP-space:

$$WTP_{attribute} = -\frac{\beta_{attribute}}{\alpha_{price}}$$

$$V_{ni} = \alpha_{price}(\boldsymbol{\beta}^{*}\boldsymbol{x_{ni}} - Price_{ni})$$

In the latter specification, the $\boldsymbol{\beta}^{*}$ values represent the marginal WTP-values for each attribute, which can again vary according to a certain distribution in the case of MMNL models.

The hybrid choice model (HCM) further extends the (M)MNL models, by adding a structural equation model (SEM) with latent variables (LV's), e.g. environmental attitude, to the model structure. The LV's are estimated in measurement models using indicators and can be subsequently included in the utility function as covariates or interaction effects (Ben-Akiva *et al.*, 2002), although they could also play a role in other parts like latent class allocation functions (Liebe *et al.*, 2018).

The relationship between the LV and its indicators, i.e. the measurement model, is most often reflective. This means that self-reported scores on the Likert-scale survey items ($\boldsymbol{I_n}$) are reflections of the respondent's true, but unmeasurable LV's with a matrix of coefficients $\boldsymbol{\Gamma}$. However, they are also subject to unknown measurement errors ($\boldsymbol{\eta_n}$) that are assumed to follow a multivariate normal distribution with zero means and an identity covariance matrix. The possibly multidimensional structure of the environmental attitude was explored using confirmatory factor analysis, which suggested that a unidimensional attitude would be best suited for estimation of the HCM. Thus, the only LV of interest in this study is the General Environmental Attitude (GEA). This results in measurement equations of the form

$$\boldsymbol{I_n} = \boldsymbol{\Gamma GEA_n} + \boldsymbol{\eta_n}$$

where $\boldsymbol{\Gamma}$ indicates the relationship between the latent variable and the scores on the indicator items. To ease interpretation of the output, the 7-point Likert scales of negatively phrased statements were reversed prior to analysis. It is therefore expected that the Preservation indicators have factor loadings with opposite signs compared to the Utilization indicators. Model identification was obtained in two ways: by fixing the variance of the LV and by fixing of a factor loading of a marker item (Raveau *et al*., 2012; Vij and Walker, 2014). This results in both a variance-scaled model and a loading-scaled model.

To determine the effect of the actual and illusory knowledge variables on the GEA, a structural equation is estimated simultaneously with the measurement and choice models:

$$\boldsymbol{GEA_n} = \psi_{AKn}\boldsymbol{Actual\ knowledge_n} + \psi_{IKn}\boldsymbol{Illusory\ knowledge_n} + \boldsymbol{\xi_n}$$

With ψ the coefficient for each knowledge variable and $\boldsymbol{\xi_n}$ a normally distributed error term, which makes the GEA a random parameter.

To conclude, the LV can be incorporated in the utility functions of the alternatives through interaction effects ($\boldsymbol{\Lambda}$) with each attribute (dummy) variable and the SQ constant, additional to the main effects ($\boldsymbol{\beta'_n}$) that follow a multivariate normal distribution as in the MMNL model. The utility function for individual *n* choosing scenario *j* in choice situation *t* can thus be written as

$$U_{njt} = \boldsymbol{\beta_n}\boldsymbol{x_{njt}} + \varepsilon_{njt}$$

$$\boldsymbol{\beta_n} = \boldsymbol{\beta'_n} + \boldsymbol{\Lambda LV_n}$$

The choice models (CL, MMNL in preference and WTP space, HCM scaled by fixing the variance and HCM scaled by fixing the factor loading of a marker item) were analyzed in R using the *Apollo* package, v.0.2.4 (Hess and Palma, 2019a, 2019b). Categorical attributes were incorporated in the models by dummy coding, with absence of the practice (and herbicide spraying for weed management) as the reference levels. The CL and MMNL models in preference and WTP-space only take the scenario attributes and choices made by the respondents into account, whereas the HCM models also incorporate interaction effects with the respondent-specific general environmental attitude (GEA) LV, the knowledge variables as predictors of this LV and a measurement model for the LV. The utility function for the SQ alternative was only characterized by the SQ constant (SQ_C) since all attributes had the reference level of dummy coding. In the MMNL and HCM models, this SQ_C could also be individual-specific and in the latter case also had an interaction effect with the GEA LV. The MMNL and HCM models were estimated using 1000 Sobol draws for each random parameter. This is only half of the recommended number of draws for choice models with similar complexity (Czajkowski and Budziński, 2019), although it is still substantially larger than in many practical applications in the literature and is seen as a compromise between required computational effort and estimation accuracy. The HCM models were only estimated in preference space. Differences in parameter estimates within models were explored with Wald tests.

3. **Results and discussion**

3.1 Descriptive sample statistics

Table 1 shows descriptive statistics of the 393 respondents. The sample is not entirely representative for the population, most probably due to the limited sample size, with total coverage of the study area resulting in oversampling of rural inhabitants. A large proportion (2/3) of the sample has a high education degree and the average age is 10 years higher than that of the population of the study area. It might be relevant that the survey was distributed in September 2020 during the SARS-CoV2-pandemic and related socio-economic measures.

Total scores on actual knowledge ranged between 0 (0/12) and 0.75 (9/12) and average actual knowledge was 0.26. Cronbach's alpha for the five most relevant items of the perceived knowledge score was 0.97, mean inter-item correlation was very high (Pearson's r, 0.86) and CFA for a construct of perceived knowledge based on the five items indicated standardized loadings larger than 0.9, justifying the use of the average score of these items to approach perceived knowledge. This variable ranged between 0 and 0.9, with an average value of 0.37. Illusory knowledge (the difference between perceived and actual knowledge) ranged between -0.67 and 0.73, with a mean of 0.11. Low subjective and objective knowledge values on sustainability issues have been observed in other studies, but with the former often exceeding the latter (Ellen, 1994; House *et al.*, 2004; Pieniak *et al.*, 2010). This might have implications for policies, since people with higher subjective knowledge could consider searching for new information unnecessary (Ruddell, 1979) and tend to ignore apparently less favorable alternatives (Brucks, 1985). If actual knowledge is high as well, this behavior can be justified, but in the case of large illusory knowledge (signifying a mismatch between perceived and actual knowledge), this could have significant consequences.

Table 1 Descriptive statistics of the survey sample, the population in the study area and the general population of Flanders.

Size (n)	Sample 393	Study area 739,450	Flanders 6,629,143		Sample 393	Study area 739,450	Flanders 6,629,143
Continuous Mean (sd)				**Categorical (%)**			
Age	53.8 (15.2)	43.1 (23.6)	42.4 (23.9)	**Gender**	52.7% Men 47.3% Women	49.6% Men 50.4% Women	49.5% Men 50.5% Women
Income level	4.252 (1.268)	3052	3015	**Landscape**	37.9% Urban 62.1% Rural	80.5% Urban 19.5% Rural	13.2% Urban 86.8% Rural
Family size	2.33 (1.06)	2.25	2.28	**Education**	31.3% Low 68.7% High	68.4% Low 31.6% High	59.4% Low 40.6% High
Actual knowledge	0.255 (0.168)	-	-	**Farmer in family**	93.9% No 6.1% Yes	-	-
Perceived knowledge	0.369 (0.222)	-	-	**Member of Env. Org.**	80.7% No 19.3% Yes	-	89% No 11% Yes
Illusory knowledge	0.113 (0.245)	-	-	**Support Env. Org.**	76.3% No 23.7% Yes	-	-

3.2 Choice models

Table 2 presents the model metrics of all estimated models. Model metrics of the full HCM models are substantially larger because of the measurement submodels, with each additional indicator inflating the absolute log-likelihood of the complete model. However, these measurement models are only indirectly linked to the choice model. When the model metrics are calculated based on the choice model log-likelihood (which also incorporates the structural relationships between knowledge and GEA), the variance-scaled HCM has the lowest AIC, BIC and AIC_C and highest (adjusted) Rho squared values, although only marginally better than the MMNL in preference-space, with the loading-scaled HCM as a close third. Burnham and Anderson (2004) suggest the use of the corrected AIC (AIC_C) for models with limited sample sizes, i.e. when $n/p < 40$ (with n = sample size and p = number of parameters to be estimated), which is relevant for the larger and more complex HCM models, although differences with AIC values are rather small.

Table 2 Model metrics for the conditional logit (CL), mixed multinomial logit (MMNL) and the two hybrid choice mixed multinomial logit models (HCM-MMNL).

	CL	MMNL (Preference space)	MMNL (WTP-space)	HCM-MMNL variance-scaled	HCM-MMNL loading-scaled
Log-likelihood (whole model)	-1867.19	-1490.75	-1497.99	-11387.57	-11396.79
Log-likelihood (choice model)	-	-	-	-1475.93	-1478.98
AIC_{Whole}	3758.38	3029.50	3043.74	22915.14	22933.57
BIC_{Whole}	3827.56	3167.87	3182.11	23407.16	23425.59
$AIC_{C,Whole}$	3758.51	3030.01	3044.25	22919.49	22937.93
$AIC_{Choice}^{\pm}$	-	-	-	3027.86	3033.96
$BIC_{Choice}^{\pm}$	-	-	-	3246.95	3253.05
$AIC_{C,Choice}^{\pm}$	-	-	-	3029.14	3035.24
Δ_{Choice}°	730.52	1.64	15.88	-	6.10
$\Delta_{C,Choice}^{\circ}$	729.37	0.87	15.11	-	6.10
Rho-square	0.2792	0.4245	0.4217	0.4303	0.4291
Adj. Rho-square	0.2746	0.4153	0.4125	0.4214	0.4202

± Metrics for the choice compartment of the hybrid choice models were calculated using the log-likelihood of the choice model and the formulas given in Burnham and Anderson (2004).

° Δ_{Choice} and $\Delta_{C,Choice}$ of a model indicate the differences in AIC and AIC_C respectively between that model (AIC_{choice} and $AIC_{c,choice}$ for the hybrid choice models) and the model with the best fit (i.e. the variance-scaled HCM).

The parameter estimates of the MMNL in preference space (Table 3) and variance-scaled HCM (Table 4) do not differ by much and result in similar conclusions. Differences are larger between the two HCM models, using different model identification techniques (Table 4), and mostly concern differences for the standard deviations and the interaction effects.

Table 5 indicates that the GEA LV is well estimated in both HCM models, with factor loadings in most cases exceeding the often used threshold value of 0.4. It appears to be positively related to items of the Preservation dimension and negatively to Utilization items, so that it captures a pro-environmental attitude.

Table 3 Parameter estimates for the MMNL models in preference and WTP-space.

	MMNL (preference space)		**MMNL (WTP-space)**	
Parameter	**μ**	**σ**	**μ_{WTP}**	**σ_{WTP}**
Status quo	-3.4957***	4.5898***	±-3.1975***	±4.7742***
	(0.5789)	(0.5655)	(0.7034)	(0.6454)
Grass strip	0.4630***	0.7505***	25.2016***	33.4580***
	(0.1299)	(0.2680)	(6.9945)	(12.0037)
Flower strip	0.8443***	0.7066***	42.2779***	18.2314
	(0.1419)	(0.2349)	(10.2264)	(18.3075)
Hedgerow-HM	1.0620***	0.6054	42.3772***	4.2053
	(0.1911)	(0.4372)	(9.6149)	(35.9756)
Hedgerow-LM	0.7076***	0.4499	29.3424***	27.0166*
	(0.1615)	(0.3726)	(8.8784)	(13.9299)
Wooded margin	1.0257***	0.0637	41.3313***	1.8388
	(0.1855)	(0.4046)	(10.0535)	(15.9542)
Mechanical weeding	1.9721***	1.5939***	92.0580***	70.0161***
	(0.2268)	(0.2097)	(15.5341)	(12.4565)
Mating disruption	0.6328***	0.9152***	31.2909***	42.8134***
	(0.1158)	(0.1870)	(7.7457)	(9.9817)
Nesting-bees	1.5928***	0.4115	76.6982***	4.6511
	(0.2064)	(0.3911)	(13.9833)	(40.1934)
Nesting-birds	1.3105***	0.6452**	57.0269***	14.7510
	(0.2040)	(0.2939)	(11.5977)	(21.3187)
Nesting-mammals	0.8829***	0.4317	41.4439***	44.2703***
	(0.1843)	(0.4458)	(11.0122)	(15.7327)
Contribution	-0.0253***	0.0414***	±(-)0.0216***	±0.0118***
	(0.0043)	(0.0068)	(0.0042)	(0.0026)

** p < 0.1, ** p < 0.05, *** p < 0.01*
***μ** and **σ** are the sample mean and standard deviation of the normal distribution of the respondent-specific parameter estimates.*
± The SQ constant and contribution parameters in the WTP-space model were estimated in preference space.
Standard errors are given between brackets.

Strong aversion for the SQ was observed in all models, but with significant and large heterogeneity. Since the SQ constant can capture other factors apart from aversion or preference for the baseline scenario (Boxall *et al.*, 2009; Oehlmann *et al.*, 2017), one should be careful with the interpretation of this value. However, as most of those factors would result in a preference for the SQ, the large, negative value observed here can indicate a general demand of the local population for the implementation of at least some nature-friendly practices on the farm. Such preferences to move away from the current situation for environmental improvement of landscapes have been observed in other studies as well (Scarpa *et al.*, 2007; Perni and Martínez-paz, 2017; Taye *et al*., 2018; Müller *et al.*, 2020). Indeed, for each of the practices that would contribute to environmental improvement, very significant positive preferences were observed. There appears to be large preference heterogeneity for several of the included practices, but not for some wooden landscape elements. Field margins with flower mixes are significantly more appreciated than grass strips ($p<0.05$). Wooden landscape elements are even more preferred (not significantly more than flower strips), although hedgerows with a low management regime were surprisingly conceived as less valuable than the other two options. A lower degree of disturbance compared to hedgerows with high management regimes provides more opportunities for fauna and flora, whereas the relatively small diameter (1.5-2 m) compared to wooded margins (5-10 m) means that the farmer has to sacrifice a smaller proportion of his land. The lower coefficient is thus rather counterintuitive. This lower preference might be the result of aesthetic considerations, since the wild growth of a hedgerow with low management regimes might be thought of as "messy", opposed to neatly trimmed hedges or larger patches of wooded vegetation. On-field practices that reduce the amount of harmful (synthetic) inputs such as herbicides and pesticides were also appreciated by the local population, indicated by the large coefficient estimates for mechanical weeding and to a lesser extent for the mating disruption technique. For mechanical weeding, the coefficient was significantly larger than all other coefficients (although only at $p<0.1$ in the case of nesting for bees). This attribute was the only one where the reference level was not "absence" but rather use of herbicides. Weed management has to occur in one way or the other on the farm, but the specific contrast between the practice and the use of potential harmful substances could have sparked a reaction in the respondents. The reference levels for the other practices were not necessarily negative. However, mechanical weeding instead of spraying of herbicides is one of the main conditions of organic farming, which is often recommended as a sustainable alternative to conventional food production (European Commission, 2020) giving rise to a demand for organically produced food (Hall *et al.*, 2004), among others motivated by environmental concerns (Rana and Paul, 2017). On the other hand, low-input practices also spark some debate among the people, as there is a large amount of heterogeneity in the observed preferences. An interesting finding is the large support for easy-to-implement measures that are not compensated through subsidies, such as creation of nesting places for fauna that can provide ESS like pollination and pest management. Nesting for bees and for birds rank second and third respectively in the coefficient estimates, only topped by the mechanical weeding coefficient, although differences between bird nesting and wooden linear elements are not significantly different. Mean preference for bee nesting was significantly different from all other mean preferences. As there is a general increase in public awareness about the problems faced by pollinators (Hall and Martins, 2020), public support for bee conservation policies is increasing (Wilson *et al*., 2017; Mwebaze *et al.*, 2018; Hall and Martins, 2020), even when knowledge about pollinators is low (Wilson *et al*., 2017).

Since the choice of the levels and non-attendance of the monetary attribute can significantly influence WTP estimates (Glenk *et al.*, 2019; Scarpa *et al.*, 2009), these values (Table 3) should not be interpreted as absolute indications of concrete payments that respondents were willing to offer, but rather in terms of relative comparisons. WTP was not estimated for the SQ constant, since its interpretation is complex and less relevant (Boxall *et al*., 2009; Oehlmann *et al.*, 2017). WTP for mechanical weeding (±€90) and nesting for bees (±€75) were found to be significantly higher than all other practices ($p<0.05$), but not different from each other. Provision of nesting for birds (±€55) was significantly more valuable than grass strips (±€25), hedgerows with low management (±€30) and mating disruption (±€30), but not than other practices (all around €40). The only other significant difference in WTP was found between grass and flower strips. The lower values for grass strips, mating disruption and hedgerows with low management regimes could result from lower familiarity with these practices. However, the findings in Table 3 indicate that there is significant willingness to financially support farmers who apply greening practices, although often with severe heterogeneity. The values are comparable to findings in the literature for interventions resulting in a biodiversity increase (Sauer and Fischer, 2010; Hynes *et al.*, 2011; Dachary-Bernard and Rambonilaza, 2012; Mwebaze *et al.*, 2018; Tienhaara *et al.*, 2020), although other price ranges have been observed as well (Colombo *et al.*, 2009; Dupras *et al.*, 2018; Bernués *et al.*, 2019). The hypothetical and experimental setting of the choice experiment warrants careful interpretation of these values.

The CFA analysis prior to specification of the HCM supported the claim that environmental attitude is a unidimensional cognitive factor, rather than multidimensional (individual attitudinal scales (Milfont and Duckitt, 2010)) or two-dimensional (Preservation and Utilization (Milfont and Duckitt, 2010; Wiseman and Bogner, 2003)). This is also clear from the HCM measurement model (

Table 5). This also supports the use of more simple tools for measuring environmental attitudes, such as the (revised) New Environmental Paradigm scale (Dunlap *et al.*, 2000; Dunlap and Van Liere, 1978) instead of the elaborate and multidimensional (although shortened) Environmental Attitude Inventory (Milfont and Duckitt, 2010; Sutton and Gyuris, 2015). Nevertheless, even with a general environmental attitude, the significant interaction effects between this LV and several attributes provide additional information in the HCM model (Table 4). Since scaling of the variance-scaled model occurred by fixing the variance of the LV to 1, the GEA is interpreted as deviations from the mean in standard deviation units. The interaction effect for the SQ constant indicates that more pro-environmental respondents have an increased aversion towards a fruit orchard that only focuses on food production. The significant (and negative) interaction effect for the monetary contribution indicates some impact of GEA on the WTP for all measures. This means that environmental attitudes not only influence one's own pro-environmental behavior (Bissing-Olson *et al.*, 2012; Okumah *et al*., 2020), but also demand and willingness-to-pay for actions by other stakeholders. Noteworthy, however, are the significant interaction effects of the attitude with both the most (mechanical weeding and nesting for bees) and the least (grass strips) preferred AEMs (based on mean main effects), but not with any of the other practices (except for hedgerows with low management at $p<0.1$). All of these significant effects are positive, so that a pro-environmental attitude correlates with increased preferences for these specific agri-environmental practices. The absence of significant interaction effects for the other practices and presence of much unexplained heterogeneity in general, suggests that preferences for agri-environmental interventions are for a large proportion influenced by non-environmental considerations, e.g. health, aesthetics and comfort. Nevertheless, for issues like a decrease in herbicides or the conservation of useful, but threatened, fauna such as bees, environmental attitude does play a role. These practices relate to hot topics in the societal debate, i.e. organic farming and the pollinator crisis. Thus, respondents may have been better acquainted with these topics and better aware of the direct relevance of the affected practices, especially if a stronger environmental attitude also results in more active participation in this societal debate. Hedgerows and field margins can also contribute to the conservation of pollinators and both types of AEM, in addition to pheromone treatment for coddle moth management and the provision of nesting places for birds and mammals can reduce the need for or negative externalities of harmful agricultural inputs. However, these relationships might be more difficult to grasp by non-farmer citizens, since they require a deeper understanding of ecological processes. The significant interaction effects for grass strips and to a lesser extent hedgerows with low management regimes appear to undermine this argument, although the added value to the respective preferences results in values that are similar to those of the other practices. This might indicate that the environmental attitude provides a common baseline demand for any agri-environmental practice, but simultaneously a higher support for mechanical weeding and nesting for bees.

Table 4 Parameter estimates for the structural part of the HCM models in preference space.

	HCM-MMNL variance-scaled			**HCM-MMNL loading-scaled (PolSupport2)**		
Variance GEA	**1**			0.9375***		
	-			(0.0739)		
Parameter	**μ**	**σ**	**λ_{GEA}**	**μ**	**σ**	**λ_{GEA}**
Status quo	-3.3633***	5.1921***	-1.2517***	-3.5325***	4.5304***	-1.4794***
	(0.6665)	(0.6303)	(0.3809)	(0.7394)	(0.5433)	(0.5001)
Grass strip	0.4740***	0.9186***	0.2957**	0.4600***	0.7389***	0.2347
	(0.1403)	(0.2434)	(0.1390)	(0.1318)	(0.2530)	(0.1499)
Flower strip	0.8340***	0.7201***	0.0887	0.8050***	0.6194**	0.0181
	(0.1458)	(0.2288)	(0.1422)	(0.1403)	(0.2634)	(0.1492)
Hedgerow-HM	1.1624***	0.6502**	-0.0636	1.0617***	0.6872**	-0.0606
	(0.2018)	(0.2604)	(0.1770)	(0.1959)	(0.2983)	(0.1868)
Hedgerow-LM	0.8476***	0.0652	0.2964*	0.8199***	0.0359	0.3723**
	(0.1730)	(0.5022)	(0.1671)	(0.1685)	(0.5723)	(0.1860)
Wooded margin	1.2100***	0.2468	0.2105	1.0492***	0.1515	0.3238*
	(0.2069)	(0.3401)	(0.1774)	(0.1923)	(0.2813)	(0.1965)
Mechanical weeding	2.0993***	1.5444***	0.9215***	1.9526***	1.3842***	1.0347***
	(0.2209)	(0.2131)	(0.1458)	(0.2017)	(0.1886)	(0.1860)
Mating disruption	0.7543***	1.0636***	0.1110	0.6858***	0.9272***	0.1688
	(0.1297)	(0.1951)	(0.1128)	(0.1179)	(0.1696)	(0.1239)
Nesting-bees	1.7995***	0.6294**	0.3889**	1.6371***	0.5690**	0.3557*
	(0.2282)	(0.2731)	(0.1668)	(0.2073)	(0.2744)	(0.1826)
Nesting-birds	1.4880***	0.5927**	0.0578	1.3028***	0.6672***	0.0204
	(0.2207)	(0.2461)	(0.1742)	(0.1982)	(0.2567)	(0.1856)
Nesting-mammals	0.9998***	0.5262**	0.0226	0.8969***	0.6356*	-0.0969
	(0.2031)	(0.2619)	(0.1968)	(0.1850)	(0.3449)	(0.2109)
Contribution	-0.0288***	0.0434***	0.0088**	-0.0257***	0.0361***	0.0098**
	(0.0048)	(0.0068)	(0.0038)	(0.0043)	(0.0076)	(0.0042)
	ψ_{GEA}			**ψ_{GEA}**		
Actual knowledge	-0.1320			0.0278		
	(0.1647)			(0.1622)		
Illusory knowledge	0.6166***			0.4845**		
	(0.1724)			(0.1918)		

** p < 0.1, ** p < 0.05, *** p < 0.01.*

***μ** and **σ** are the sample mean and standard deviation of the normal distribution of the respondent-specific parameter estimates for the main* *effects.*

λ_{GEA} are the interaction effects, indicating the parameter change for respondents with a GEA value 1 standard deviation from the mean (variance-scaled HCM) or with a GEA value that causes a shift of 1 Likert-scale point from the mean score on the PolSupport2 item (loading-scaled HCM).

ψ_{GEA} denotes the coefficients of the effects of actual and illusory knowledge on the environmental attitude.

Standard errors are given between brackets.

Table 5 Parameter estimates of the measurement submodels of the variance-scaled and loading-scaled GEA HCM.

HCM-MMNL measurement models Loadings GEA (γ)

variance-scaled									
Preservation						***Utilization***			
Ecocentric concern		***Environmental fragility***		***Policy support***		***Altering nature***		***Human utilization of nature***	
I1	0.8693*** (0.0748)	**I1**	0.5287*** (0.0650)	**I1**	0.6588*** (0.0499)	**I1**	-0.7857*** (0.0709)	**I1**	-0.7537*** (0.0602)
I2	0.3762*** (0.0542)	**I2**	0.8791*** (0.0724)	**I2**	0.8963*** (0.0705)	**I2**	-0.5950*** (0.0671)	**I2**	-0.7000*** (0.0665)
I3	0.7201*** (0.0674)	**I3**	0.8123*** (0.0840)	**I3**	0.5766*** (0.0979)	**I3**	-0.8738*** (0.0685)	**I3**	-0.9617*** (0.0619)
						I4	-0.7446*** (0.0853)		
loading-scaled (PolSupport2)									
Preservation						***Utilization***			
Ecocentric concern		***Environmental fragility***		***Policy support***		***Altering nature***		***Human utilization of nature***	
I1	0.9379*** (0.1022)	**I1**	0.5839*** (0.0823)	**I1**	0.7145*** (0.0726)	**I1**	-0.8670*** (0.0964)	**I1**	-0.8360*** (0.0854)
I2	0.3916*** (0.0657)	**I2**	0.9544*** (0.1026)	**I2**	**1** -	**I2**	-0.6547*** (0.0855)	**I2**	-0.7643*** (0.0886)
I3	0.7707*** (0.0893)	**I3**	0.9128*** (0.1112)	**I3**	0.6378*** (0.1150)	**I3**	-0.9706*** (0.0970)	**I3**	-1.0521*** (0.0974)
						I4	-0.8069*** (0.1084)		

** p < 0.1, ** p < 0.05, *** p < 0.01*

Awareness and understanding of the requirements and implications of agri-environmental practices are important to justify the high demand for them observed in this study. However, both observed and self-stated knowledge appears to be low. More specifically, no direct effect of actual knowledge on the environmental attitude was found (Table 4), but it might play a role since it is involved in the calculation of the illusory knowledge score, which exhibits a significant and positive relationship with GEA. A similar gap between awareness and interest in bee species was observed in Wilson *et al.* (2017). Given the data and based on the HCM, causality of the relationship between environmental attitude and illusory knowledge cannot be determined. It might be possible that respondents claim to be more knowledgeable in order to motivate a more extreme environmental attitude and stronger preferences for AEM. However, illusory knowledge could also result from false beliefs or erroneous self-assessment (Kruger and Dunning, 1999), which was indeed observed in the responses on the actual knowledge questions. Respondents often selected the wrong answer instead of the "*I don't know*" option. Since large illusory knowledge might impede information search behavior or result in active ignorance of contradicting information (Brucks, 1985; Ruddell, 1979), this can result in more extreme opinions and attitudes. Environmental attitudes and preferences for agri-environmental measures might thus be susceptible to biases, ignorance and misconceptions, rather than formed by rational considerations. If this is the case, it will have consequences with regards to the salience and role of the societal debate in agri-environmental policies.

The relatively small sample did not result in overfitting of the complex HCM, since it receives approximately similar levels of support as the commonly used MMNL model (Table 2). Some sample characteristics deviate from the reference population (Table 1), most specifically the proportion of rural residents, age and education level. The deviation for the proportion of rural residents can be attributed to differences in measurement, i.e. self-stated assessment of the living environment in the survey versus a combination of population densities and the CORINE dataset in the population. Stronger reservations concerning the findings of this study are warranted by the age difference and education level. Older people may have stronger feelings of place attachment (García-Martín *et al.*, 2018) and subsequently concern for sustainable landscape management, in addition to a better understanding of the increasing agricultural intensification due to a longer reference period. The higher education levels observed in the survey sample can result from self-selection bias, since people with higher education are assumed to be more interested in topics of sustainability (Gifford and Nilsson, 2014). However, the role of environmental attitude, which assumedly also relates to interest in sustainable issues, in the expression of preferences for the specific practices was found to be rather limited, thereby reducing the influence of self-selection bias in the model outputs.

4. **Conclusion**

Local inhabitants of rural areas consider agri-environmental practices applied by farmers as valuable contributions to the landscape and environment. However, preferences for specific practices vary significantly, partially explained by a unidimensional environmental attitude. Most preferred were the practices that have well-known consequences for nature and society, e.g. a decrease in harmful inputs, protection of valuable and observable species, like pollinators and birds, and to a lesser extent the many ecosystem services provided by wooden landscape elements. However, public objective knowledge on these practices is rather limited and it is mostly illusory knowledge that shapes a pro-environmental attitude. This provides difficulties for policy-makers, since information campaigns will not have the desired effects by merely increasing knowledge or awareness. Addressing common misconceptions and alleviating biases in society may result in less stringent demands, but farmers can perceive this as more trust in and acceptance of their skills and experience and thus a motivation for enhanced participation. Connecting farmer and non-farmer stakeholders in the rural landscape could increase (farmer awareness of) social appreciation and support for farmer's efforts. Future research could further investigate the role of illusory knowledge and the suggestion of a Dunning-Kruger effect on public support and demand for sustainable agriculture and study the public's perceived linkages between agri-environmental practices, ecosystem services and (non-ecological) benefits for farmers and non-farmers.

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