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Full Research Article

Does the place of residence affect land use preferences? Evidence from a choice experiment in Germany

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Abstract. Discrete choice experiments can be used to inform policy makers on people's preferences for landscapes and cultural ecosystem services. Recent studies have shown that the spatial context influences preferences and related willingness to pay values. In this paper we investigate the effect of the landscape surrounding people's places of residence on their willingness to pay using data from a discrete choice experiment on local land-use changes and cultural ecosystem services throughout Germany. For analysis, we apply a latent class logit model and include landscape categories as explanatory variables for class membership. We find that the different landscapes people live in are correlated with preferences. Especially people from urban areas and farm- and grassland landscapes have larger willingness to pay values for improvements in cultural ecosystem services than people from forest landscapes and cultural landscapes. The results are important for policy makers as different willingness to pay values in different landscapes imply different welfare effects for land use changes. Taking this information into account can help in reaching more efficient resource allocations.

Keywords. Landscape preferences, latent class model, spatial heterogeneity, willingness to pay.

JEL Codes. Q51, Q57.

1. Introduction

Policy makers at different scales initiate land use changes to conform with subordinated laws and guidelines. Decisions should balance social and private costs and benefits for different stakeholder groups and the local population. Rigorous cost-benefit analysis is often difficult to conduct, as most regulating and cultural ecosystem services that are produced by landscapes are not traded in markets, making it impossible to directly observe societal demand for them. Benefit estimates of changes in ecosystem service provision need to be inferred through the use of non-market valuation techniques; in particular stated

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preference methods, which allow estimation of willingness to pay through direct elicitation of preferences in hypothetical markets. In Europe, several non-market valuation studies assessing preferences for components and management of agrarian landscapes have been conducted, but they rarely accounted for spatial differences in preferences (Zanten et al. 2014; Glenk et al. 2019). The few studies that considered spatial heterogeneity in preferences found that the place of residence of respondents in stated preference surveys influences willingness to pay estimates (Campbell, Scarpa, and Hutchinson 2008; Campbell, Hutchinson, and Scarpa 2009; Brouwer, Martin-Ortega, and Berbel 2010; Broch et al. 2013; Garrod et al. 2012; Johnston and Ramachandran 2014). As land-use changes are often conducted locally, such information can significantly impact the results of cost-benefit analyses and may reveal insights on where a land-use change offers the largest benefits.

This paper contributes to the literature on spatial preference heterogeneity by investigating how preferences for policy-relevant landscape attributes differ across respondents residing in different landscapes. Spatially-driven differences in preferences for changes in landscape attributes can occur for two main reasons. First, it is well-established that individual preferences are affected by the current level of endowment (Glenk 2011; Hess, Rose, and Hensher 2008; Tversky and Kahneman 1981). Therefore, an increase or decrease in a good is valued relative to this status quo situation. Because the marginal value of a good or service may not be constant over levels of provision, individuals with different status quo situations may value additional changes in provision differently. In particular, economic theory suggests that the utility or value that is attributed to an additional unit of a good or service is higher if its scarcity increases. The concept of diminishing marginal utility suggests, for example, that people residing in a forest landscape are willing to pay less for additional forest area created than individuals living in farm- and grassland landscapes with little forest cover (Sagebiel, Glenk, and Meyerhoff 2017). Diminishing marginal utility may apply if more of a good or service is always preferred over less; however, this may not always apply to landscape attributes, where optimal shares of certain land use shares and landscape elements may exist. That is, an increase in land use share may be perceived beneficially up to a threshold, beyond which utility for an additional increase in provision decreases (Schmitz, Schmitz, and Wronka 2003).

Second, the overall composition of a landscape has a unique value that is qualitatively different from other landscapes and that is difficult if not impossible to describe in terms of separate landscape attributes. That is, residents have different perceptions of landscapes and of the role that specific elements play in achieving uniqueness. Consequently, preferences for changes in landscape attributes may differ across landscape types, either in a systematic fashion in case that subjective perceptions of landscape amenity and value are similar across individuals living in a particular landscape type, or in an unpredictable way if there is considerable heterogeneity in perceptions. For example, those individuals living in forest landscapes may have a systematically greater demand for enhancing biodiversity, whereas people living in farm- and grassland landscapes may prefer additional structural elements. Similarly, some people living in farm- and grassland landscapes may perceive their openness as a cultural heritage characteristic of a particular region, thus objecting structural change.

In the paper, we investigate the correlation between residing in different landscape categories (i.e., different status quo situations) and preferences for changes in landscape attributes, for example share of forest or levels of biodiversity. We use data from a web-based discrete choice experiment (DCE) survey in Germany to empirically test if differences in willingness to pay for landscape attributes exist; and if the 'status quo' landscape serves as a reference point for choices in the DCE with impacts on willingness to pay estimates.

The results are relevant for policy makers dealing with local land-use changes and researchers considering DCEs to assist cost-benefit analyses. For example, in Germany, there is a discussion about combating climate change by increasing the share of energy crops for renewable energy generation. A policy maker can set spatially varying incentives or other policy tools aiming at increasing or decreasing the share of corn on agricultural fields. Typically, such incentives are based on private benefits and ecological constraints, e.g. where gross margins are high. Social welfare impacts associated with landscape change are often not considered at all, or are not directly compared with private costs and benefits. Additionally, the importance of acceptance of the land use change by the local population is often neglected, and willingness to pay values, distinguished by landscape categories, can help to identify areas where such a land-use change is likely to find local support.

2. Survey and Data

2.1 Data Collection and Discrete Choice Experiment

The DCE is part of a German-wide, web-based survey conducted in March 2013. The respondents were recruited from an online panel of a large international market research institute. People 18 years or older who resided in Germany at the time of the study were eligible to participate. The survey consists of the six sub-samples with different DCEs, totalling around 10,000 respondents. The DCEs differ in their attributes and had different land-use foci. In all samples, the scenario was a local land use change within a radius of 15 km around the respondent's place of residence. The radius should represent a typical distance for everyday activities. We discussed the radius in focus groups and came up with 15 km being a widely accepted distance. Besides the DCE, the survey includes questions on leisure activities, perceptions and knowledge on land use and climate change as well as socio-demographic variables. Respondents were requested to provide their postal code or to use the integrated geo-tool which supplies the coordinates of the places identified by respondents such as their residence location.

In this paper, we use a sub-sample with attributes related to agricultural land-use changes. The DCE comprises five non-monetary attributes each having three levels, with zero indicating the status quo as today. Table 1 gives a description of all attributes of the used sample as well as the dummy codes used in the analysis.

The first attribute *Forest* refers to the share of forest. It takes the values *as today*, *10% less* and *10% more*. We assume that an increase in forest area increases utility with a decreasing rate (diminishing marginal utility). That implies that people living in forest rich areas gain less utility from an increase in forest than people living in areas with a low share of forest. The second attribute *Fieldsize* describes the average size of fields and forests. The levels include *as today*, *half the size of today* and *double the size of today*.

Table 1. Attribute description.

Attribute	Description	Levels	Dummy Code
Forest	Share of forest in %	as today 10% decrease 10% increase	omitted ForMinus10 ForPlus10
Fieldsize	Average size of forest and fields	as today half the size double the size	omitted FieldHalf FieldDouble
Biodiversity	Degree of biodiversity measured with bird indicator	as today (55 Points) slight increase (85 Points) strong increase (105 Points)	omitted Bio85 Bio105
Cornshare	Share of corn on agricultural fields	as today share of 30% share of 70%	omitted Corn30 Corn70
Meadows share	Share of meadows in %	as today share of 25% share of 50%	omitted Mead25 Mead50
Price	Annual payment to a local landscape fund in Euro	0, 10, 25, 50, 80, 110, 160	

Smaller field sizes imply a less monotonic landscape and more structural elements, which are assumed to be more attractive in terms of visual amenity (Zanten et al. 2014). On the other hand, larger forests can lead to better forest connectivity which may have positive implications for biodiversity and recreation. We therefore have no clear expectation for this attribute. The third attribute *Biodiversity* is described with a bird indicator as a proxy for biodiversity. Bird indicators are used in several countries as headline indicators for biodiversity (Gregory et al. 2003; Butchart et al. 2010). The bird indicator, developed by the German Federal Agency for Nature Conservation, provides information on the suitability of the area for birds, where 100 points describe the state in the year 1975 in Germany (Doerpinghaus and Ludwig 2005). For Germany as a whole, the bird indicator is currently estimated to lie at about 55 points. The levels used in the DCE are *as today (55 Points)*, *slight increase (85 Points)* and *strong increase (105 Points)*. We expect that utility increases with increasing points, as it has been found in other DCE studies (Shoyama, Managi, and Yamagata 2013). The fourth attribute *Cornshare* is the share of corn on agricultural fields. The levels are *as today*, *30%* and *70%* on the agricultural fields in the surrounding. In the focus group discussions conducted prior to the survey, corn was often described as having a negative impact on landscape. We expect that a larger share of corn leads to a decrease in utility. *Meadowsshare*, the fifth attribute, refers to the share of meadows and grassland used for grazing. It takes the levels *as today*, *25% of the area*, *50% of the area*. In the focus group discussions, most participants linked a high share of meadows to a more natural landscape. We thus expect a utility increase from an increase in the share. Note that some attribute levels imply a reduction in the endowment compared to the status quo. This is explicit for Forest and Fieldsize and implicit for Cornshare and Meadowsshare. In the former case, we expect that some respondents have preferences for a

Figure 1. Example of a choice set.

If only the following options were available for the future development of the landscape within a radius of up to 15 kilometers around your place of residence, which one would you choose? If you live in a large city, please consider the surrounding area of the city.

		Landscape A	Landscape B	Landscape C
	**Share of forest**	As today	Increase by 10%	As today
	**Field size**	As today	Twice the size	As today
	**Biodiversity on agricultural fields**	Strong increase	As today	As today
	**Share of maize on arable land**	max. 70% of fields	max. 30% of fields	As today
	**Share of grassland on agricultural fields**	25%	25%	As today
	**Financial contribution to fund per year**	110 €	80 €	0 €
I CHOOSE ☑		☐	☐	☐

reduction. For example, in forest rich areas, people may prefer a reduction in forest share (Sagebiel, Glenk, and Meyerhoff 2017). To account for such preferences, we used a positive and a negative level. In the case of Cornshare and Meadowsshare, the direction of the change (reduction or increase) depends on the respondent's current situation. However, absolute percentage values are useful as, in practice, land use changes are often announced in such values. We expected that people understand an absolute percentage value better than a relative change. Thus we used absolute percentage values for these attributes, taking into account that the change people value varies between respondents. Finally, the price attribute is framed as an annual payment to a newly introduced landscape fund per person for an unspecified period of time. We explained to the respondents that all residents who are affected by the land use change will have to contribute to the fund (i.e. a compulsory payment) and that the money in the fund was to be exclusively used to finance and maintain the land use changes. The exact description of the payment vehicle was informed by focus group discussions. The framing of the payment vehicle as a fund was preferred to other possible payment vehicles and regarded as credible. Tax payments were not regarded as credible, because the land use change was local while taxes are usually collected at least at county level and often used for multiple purposes. The levels of the fund range from 10 to 160 Euro and is set to szero in the status quo alternative.

Each choice set consists of three unlabelled landscape alternatives, where *landscape 3* represents the status quo (Figure 1). The experimental design was created with the software package NGene, maximizing C-efficiency, which relates to the minimization of variance of willingness to pay estimates. The design was optimized for a multinominal logit model with linearity in utility and priors close to zero. It consisted of 18 choice sets divided into two blocks. Each respondent answered nine choice sets. The order of the choice sets was randomized across respondents.

2.2 Landscape categories and socio-demographics

The German Federal Agency for Nature Conservation has developed a system to classify landscapes within Germany. The intention behind this approach is to provide a basis for effective conservation and development of cultural landscapes along the objectives of the European Landscape Convention. Overall, the German land surface was divided in 858 landscapes including 59 urban conglomerations. The system comprises overall 24 landscape types that are assigned to the following six main categories (Gharadjedaghi et al. 2004):[1]

1. Coastal landscapes: This type is characterized by landscapes near the German coast of the North Sea and the Baltic Sea.
2. Forest landscapes: These landscapes have a large share of forests between 40% and 70%.
3. Cultural landscapes: These landscapes have a share of forest between 20% and 40% and a high share of one of the following items: water bodies, meadows and grassland, wine-growing, glaciers and rocks, orchards, wetlands, a combination of the items.
4. Farm- and grassland dominated landscapes: In contrast to the cultural landscapes, they have a share of forest that is less than 20%. They are further characterized by a large share of grassland and arable land.
5. Mining areas: Landscapes with more than 10 percent of the land surface under open cast mining.
6. Urban agglomerations: These landscapes comprise cities and areas with a high density of settlements and infrastructure.

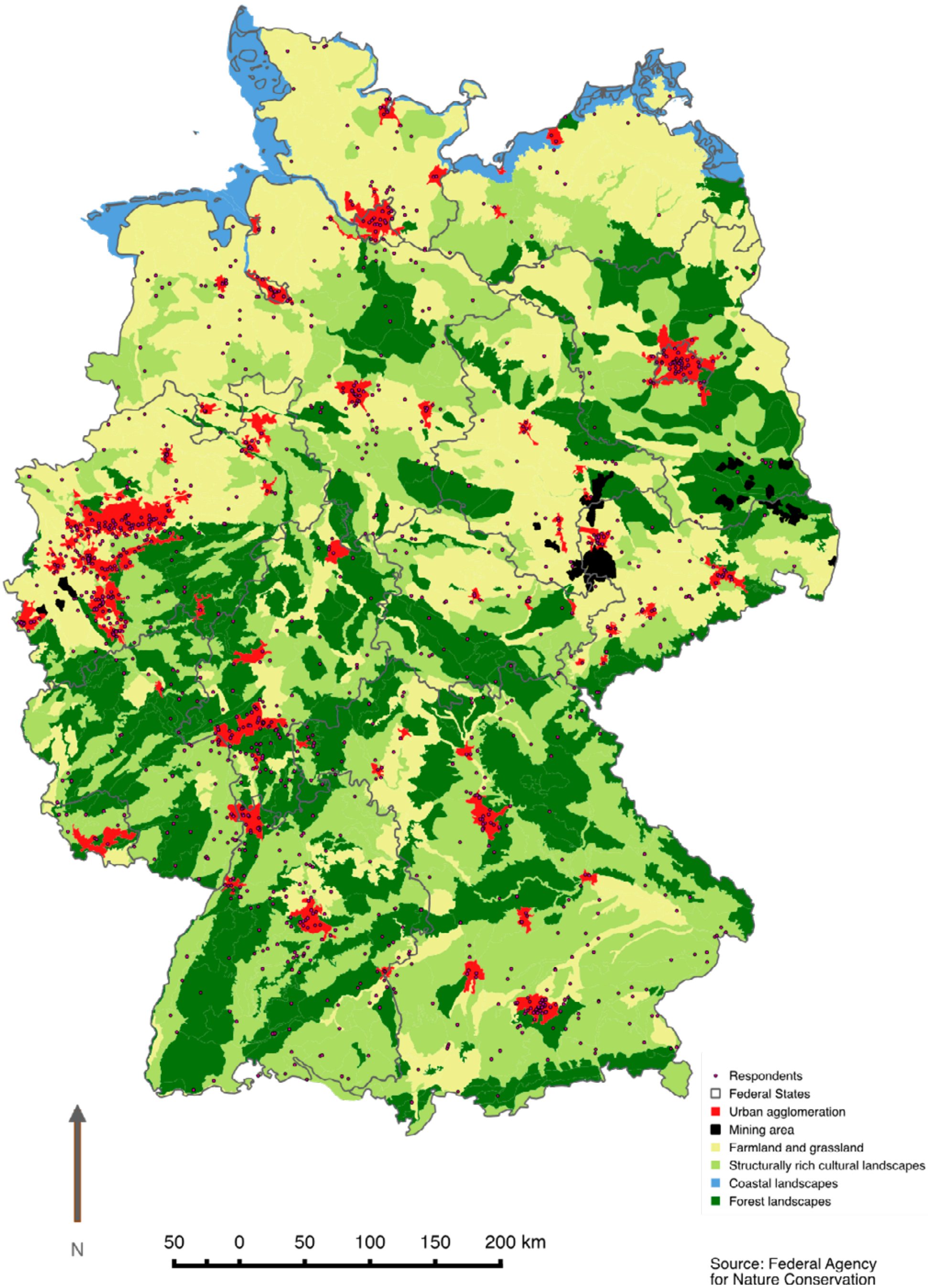
Table 2 summarizes the distribution of the respondents according to the landscapes. Each respondent is uniquely allocated to one of the categories. In this process, the actual place of residence was used to determine the landscape category rather than the percentage share of landscape categories surrounding the place of residence. Figure 2 maps both the landscape categories and the respondents' locations. We exclude five respondents from coastal landscapes and mining areas from the analysis as these categories are too small. The final sample size is 1409.

Table 2. Distribution of landscape categories.

Landscape Category	No.	%
Coastal landscapes	3	0.2
Forest landscapes	204	14.4
Cultural landscapes	326	23.1
Farm- and grassland landscapes	309	21.9
Mining areas	2	0.1
Urban Agglomerations	570	40.3
Total	1414	100.0

[1] See https://www.bfn.de/en/activities/protecting-habitats-and-landscapes/landscapes-of-conservation-importance/landscape-types.html for a brief description of the 24 landscape types.

Figure 2. Spatial distribution of sample.



2.3 Hypotheses and empirical strategy

The geo-referenced respondents are distinguished by the landscape categories described in Table 2. The main aim is to find out whether respondents from different landscapes exhibit different preferences. Hence, the main hypothesis is: preferences and willingness to pay values for landscape attributes correlate with the landscape in which a respondent lives.

We expect decreasing marginal utility, i.e. marginal willingness to pay is lower in landscapes where the status quo levels of defining attributes are already high. For example, marginal willingness to pay for more forest is lower in forest landscapes than in the other landscape categories. Additionally, we expect some kind of place attachment for attributes that dominate a landscape (Scannell and Gifford 2010). For example, a respondent living in a forest rich area is not willing to give up forest as it is a dominant characteristic of the landscape. In contrast, a respondent living in an area with a medium share of forest is more interested in gaining forest but also less averse against a loss in forests. Table 4 shows that in farm- and grassland landscapes, fieldsize is higher than in the other categories, where it is rather similar. Hence, the hypothesis is that the willingness to pay for half the size differs between farm- and grassland landscapes and the other landscapes. Corn share is highest in the two cultural landscapes and lowest in urban agglomerations. As a high corn share is expected to be perceived negatively, and for most respondents the first level already implies an increase over the status quo, we expect negative willingness to pay values. These would be highest in cultural landscapes and lowest in urban agglomerations. Therefore, we focus on the second level of this attribute, i.e. an increase to 70%. The average share of meadows is relatively similar in all landscapes, so that large differences in willingness to pay may not be present.

3. Econometric approach

In the analysis, we use a latent class logit model to investigate the effects of the landscape categories on preferences and willingness to pay. The model is consistent with microeconomic theory, assuming rational individuals who maximize a utility function under constraints. An individual i chooses in t choice situations between a given set of alternatives n – each described by a conditional indirect utility function U_{int} – the alternative that provides the maximum amount of utility. Each alternative is characterized by k attributes that have levels A_{iknt}. We assume the utility functions for alternatives to be linear and additive in the attributes, and add an error term e_{int} which is Extreme Value Type I distributed to the random utility model. A utility function can be written as

$$U_{int}=beta_1 A_{i1nt}+\beta_2 A_{i2nt}+\ldots+\beta_k A_{iknt}+e_{int} \tag{1}$$

where the β_ks are the corresponding utility coefficients. The probability of an individual choosing alternative n can be written as a conditional logit model:

$$Pr_{imt}=\frac{exp(\beta_1 A_{i1mt}+\beta_2 A_{i2mt}+\ldots+\beta_k A_{ikmt})}{\sum_{n=1}^{N} e\,xp(\beta_1 A_{i1nt}+\beta_2 A_{i2nt}+\ldots+\beta_k A_{iknt})} \tag{2}$$

This model has a closed form and can be estimated using maximum likelihood.

In order to incorporate preference heterogeneity, we apply a latent class logit model. We assume that a given number of preference classes S, differing in their utility parameters $<\beta_{k|1},\beta_{k|2},\ldots,\beta_{k|s}>$, exists. Each individual has probabilities $<h_1,h_2,\ldots,h_s>$ to be member of the preference classes. The probabilities h_s can be estimated with a multinomial logit model

$$h_s = \frac{exp(\zeta_s X_i)}{\sum_{s=1}^{S} e\,xp(\zeta_s X_i)} \tag{3}$$

where X_i are explanatory variables, in this case the landscape categories, and ζ_s are the coefficients. The unconditional choice probability to choose alternative m is given as

$$Pr_{imt} = \sum_{s=1}^{S} h_s Pr_{imt|s} \tag{4}$$

The latent class logit model as described in equation 4 introduces preference heterogeneity between classes. Within a class, preferences are fixed. To relax this assumption without introducing a large amount of new parameters, we extend the model to a scale-adjusted latent class model (Magidson and Vermunt 2008). In this model, each preference class s is separated by a constant which can be interpreted as a scale parameter. The scale parameter merely states that preferences for all attributes are higher in the one scale class than in the other scale class. Whether the differences between respondents are caused by different preferences (all very high, vs. all very low) or by differences in the error variances (more random vs. less random choices) cannot be answered empirically (Hess and Train 2017). Still, the introduction of this parameter captures another dimension of heterogeneity, which can improve model fit significantly. As the scale classes are restricted in a way that all preference parameters differ similarly, willingness to pay values between scale classes are not affected. Technically, the scale parameter is estimated by another multinomial logit model, and each respondent has a probability g to belong to scale class r – similar to the preference classes. The unconditional choice probability in equation 4 becomes

$$Pr_{imt} = \sum_{s=1}^{S}\sum_{r=1}^{R} g_r h_s Pr_{imt|sr} \tag{5}$$

If an earlier analysis has already identified some respondents belonging to a specific class, one can add a known-class parameter τ_r. This parameter is zero if a respondent cannot be assigned a priori to a certain class, leading to

$$Pr_{imt} = \sum_{s=1}^{S}\sum_{r=1}^{R} g_r h_s \tau_r Pr_{imt|sr} \tag{6}$$

In this study, we use the known class indicator to classify all respondents who have always chosen the status quo option into class 1. To determine the number of preference classes *S*, one can use statistical measures of fit such as the Bayesian Information Criterion (BIC), or the corrected Akaike Information Criterion (cAIC). Both BIC and cAIC penalize for more parameters and are therefore preferred over other information criteria. Additional to the statistical criteria, one can rely on own judgment concerning reasonable parameter estimates and knowledge gained from earlier analyses (Boxall and Adamowicz 2002; Scarpa and Thiene 2005).

To calculate willingness to pay values for each class individually, the respective class preference parameter is divided by the class cost parameter. Confidence intervals of willingness to pay are calculated with the delta method.

4. Results

4.1 Descriptive statistics of landscape categories

We first analyze the relationship between socio-demographic variables and landscape categories. This step is important to understand whether and how potential differences in preferences could arise from differences in socio-demographics rather than the landscape respondents are living in.

Most differences are found between urban agglomerations and the other landscapes (Table 3). Respondents from urban agglomerations are more educated and have fewer children. We use Kruskall-Wallis and t-tests to test for overall differences between the landscape categories. Statistically significant differences on a 5% level are present for all variables except personal income and sex. Although there are differences in socio-demographics between landscape categories (especially between urban areas and all other areas), we will not investigate those here. We acknowledge that the differences in preferences may be driven by socio-demographics rather than landscape categories, but this is not relevant for the policy question of how land use changes are perceived in different landscapes. Our analysis thus only provides correlations.

Using data from the German Federal Agency for Cartography and Geodesy (BKG) and the German Federal Institute of Research on Building, Urban Affairs and Spatial Development (BBSR), we investigated the actual status quo attribute levels of the respondents. Table 4 summarizes the actual status quo in the 15km radius by landscape categories. In most cases, there are relatively large differences between the landscape categories. For the sake of parsimony, we will not investigate the actual status quo and possible effects any further. Sagebiel, Glenk, and Meyerhoff (2017) conduct a detailed investigation of the actual status quo and its effects on willingness to pay.

4.2 Latent class analysis

We estimate the latent class model described in section 3 using the software package LatentGold Choice 4.5 with the Syntax module. To select a specific number of classes we compared BIC and cAIC for two to eight class models, in the absence and presence of a scale class. We choose a model with five preference classes and two scale classes. This model turned out have the lowest BIC and cAIC values and offered plausible parameter values.

Table 3. Frequencies and column percentages (in parentheses) of socio-demographic variables.

	Forest	Cultural	Farm- and grassland	Urban	Total
Education					
Secondary or less	83 (40.9)	122 (37.4)	121 (39.4)	141 (24.7)	467 (33.2)
Higher education	46 (22.7)	86 (26.4)	77 (25.1)	155 (27.2)	364 (25.9)
University	74 (36.5)	118 (36.2)	109 (35.5)	274 (48.1)	575 (40.9)
Sex					
Male	100 (49.0)	168 (51.5)	175 (56.6)	308 (54.0)	751 (53.3)
Female	104 (51.0)	158 (48.5)	134 (43.4)	262 (46.0)	658 (46.7)
Children in household					
Yes	68 (33.3)	135 (41.4)	102 (33.0)	134 (23.5)	439 (31.2)
No	136 (66.7)	191 (58.6)	207 (67.0)	436 (76.5)	970 (68.8)
Income					
Less than 1500 Euros	81 (39.7)	128 (39.3)	120 (38.8)	227 (39.8)	556 (39.5)
1500 to 2600 Euros	58 (28.4)	91 (27.9)	74 (23.9)	153 (26.8)	376 (26.7)
More than 2600 Euros	65 (31.9)	107 (32.8)	115 (37.2)	190 (33.3)	477 (33.9)
Age					
19 to 29	32 (15.7)	67 (20.6)	60 (19.4)	132 (23.2)	291 (20.7)
30 to 39	50 (24.5)	62 (19.0)	58 (18.8)	110 (19.3)	280 (19.9)
40 to 49	39 (19.1)	89 (27.3)	92 (29.8)	144 (25.3)	364 (25.8)
50 to 59	40 (19.6)	64 (19.6)	55 (17.8)	102 (17.9)	261 (18.5)
Older than 60	43 (21.1)	44 (13.5)	44 (14.2)	82 (14.4)	213 (15.1)

All attributes except price were dummy coded with the status quo level *as today* as the reference. The landscape categories entered the class membership function as dummy coded variables with forest landscapes as the reference category. We did not include any socio-demographic variables as these are correlated with the landscape categories,

Table 4. Mean and standard deviation (in parenthesis) of actual status quo by landscape categories.

	Forest	Cultural	Farm- and grassland	Urban	Total
Forest Share	41.7	29.8	17.5	18.4	24.2
	(12.2)	(11.2)	(9.7)	(10.0)	(13.7)
Field Size	17.7	17.5	25.9	17.0	19.2
	(7.5)	(6.8)	(12.2)	(6.7)	(9.1)
Corn Share	14.9	20.9	19.9	10.5	15.5
	(10.3)	(14.8)	(15.8)	(10.0)	(13.5)
Meadows Share	15.6	17.9	18.1	12.6	15.5
	(6.1)	(9.0)	(12.1)	(7.1)	(9.1)

potentially causing multicollinearity. 23% of all respondents chose the status quo alternative in all choice situations and were assigned to class 1 with a probability of 1. As several respondents seemed to have ignored the price attribute, we fixed the price parameter to zero in class 3 to capture price non-attendance. In models without this restriction, at least one class is characterized by willingness to pay values three times as high as the highest price level of 160 Euro, which we consider implausible.

In a first step, we describe the five classes in terms of estimated utility parameters and willingness to pay values. Then, we investigate the relationship between class membership and landscape categories. Table 5 shows the estimation results and Table 6 its willingness to pay values.

The overall model is highly significant. The statistically significant coefficient for the scale class of -0.302 translates to scale class probabilities of 57.5% and 42.5% for scale classes 1 and 2, respectively, indicating that additional heterogeneity and correlation patterns are present. In Class 1, price, ForMinus10, FieldHalf, FieldDouble, Corn70 and Mead50 are highly significant and negative. Willingness to pay values range between -88 and -35 Euro, i.e. people are opting against all land use changes and would need to be compensated. The positive and significant ASCsq means that Class 1 is characterized by preferences towards the status quo. Class 2 has a negative and significant ASCsq, indicating preferences for land use changes. ForMinus10, ForPlus10, FieldDouble, Bio105, Corn70, Mead50 and price are significant with the expected signs. The willingness to pay for ForMinus10 and ForPlus10 is -165 Euro and 64 Euro, respectively. People are willing to pay for increases in forest, but would need to be compensated nearly three times as much for decreases in forest. For a reduction of field sizes (FieldHalf), willingness to pay is nearly 20 Euro while a doubling of field sizes would need to be compensated with 45 Euro. Willingness to pay for increases in biodiversity is 32 Euro for an increase to 85 points and 51 Euro for 105 points. A share of corn of 30% is not significant but a share of 70% requires a compensation of 61 Euro. Willingness to pay for a share of meadows of 25% is positive (42 Euro) while a share of 50% is not significant and close to zero. In summary, Class 2 is characterized by large positive and negative willingness to pay values for land use changes. Class 3 is the price non-attendance class. Respondents who disregard the cost attribute are likely choosing a land use change scenario over the status quo if they

Table 5. Latent class model with five classes.

	Class 1	Class 2	Class 3	Class 4	Class 5
ASCsq	0.760	-1.281***	-23.897**	-3.993***	-3.535***
ForMinus10	-3.151***	-4.169***	-17.829*	-1.287***	-0.062
ForPlus10	-0.316	1.624***	0.926***	0.317*	1.108**
FieldHalf	-2.678***	0.474	-0.075	-0.961***	-1.305***
FieldDouble	-2.120***	-1.132***	-0.275**	0.390**	-0.361
Bio85	0.774	0.814**	-5.791**	0.444	-0.455
Bio105	0.431	1.295***	1.233***	0.103	0.964*
Corn30	-0.647	0.592	1.055***	0.038	0.351
Corn70	-5.326***	-1.563***	0.214	-1.195***	-0.763
Mead25	-1.173	1.056***	-0.035	-1.120***	-1.503***
Mead50	-2.525***	0.090	0.773***	-0.802***	-0.586
price	-0.060***	-0.025***	0.000	-0.013***	-0.078***
Covariates of membership function					
Forest	ref	ref	ref	ref	ref
Cultural	ref	0.172	0.877**	0.041	0.924*
Grass/Farm	ref	0.655**	1.245***	0.2462	1.167**
Urban	ref	0.198	1.326***	0.438	1.325***
Scale classes					
	Scale Class 1	Scale Class 2			
Constant	ref	-0.302**			
Log-Likelihood	-8976.153				
Observations	12681				
Respondents	1409				

* p < 0.10, ** p < 0.05, *** p < 0.01 , ref = reference category with parameter fixed to zero

have a positive attitude towards policy change. This is reflected in the very large and negative ASCsq. Similarly, the very large and negative coefficient for decreases in forest share can be explained by this phenomenon. Nearly all coefficients of the remaining attributes are significant and have the expected signs. Bio85 is significant and negative which could imply that members of this class have already a high degree of biodiversity and regard 85 points as a deterioration. Similarly, the positive coefficient of Corn30 implies that people have already high shares of corn and regard a 30% share as an improvement. Finally, Mead25 is not significant while Mead50 is significant and positive. Class 4 is characterized by comparatively large negative willingness to pay values to avoid decreases in forest share, field size and a corn share of 70%. Interestingly, the willingness to pay for meadows share is negative for both 25% and 50%. In Class 5, positive willingness to pay values are significant and positive only for ForPlus10 (14 Euro) and Bio105 (12 Euro) and negative for FieldHalf (-16 Euro) and Mead25 (-19 Euro). This class comprises small or no utility gains from land use changes.

The landscape categories have a significant impact on the probability to be member of a class. Forest landscapes and Class 1 are the reference categories, the parameters in the membership function are interpreted relative to them. Class 1 is the largest class with a share of about 40%. Classes 2 to 4 have a share between 16% and 19%. Class 5 is the smallest class with a share of 9%. Note that Classes 1 and 5 are characterized by no or low willingness to pay values and make up nearly 50% of class membership.

Table 7 shows class membership probabilities calculated for each landscape category separately. Differences in class membership between landscape categories are present in Classes 1, 3 and 5. Membership probabilities are rather homogeneous for Classes 2 and 4. Respondents from forest landscapes are more likely to be member of Class 1 compared to the other categories with a share of nearly 51% (against the class average of 39%) and less likely member of Classes 3 and 5 with shares of only 8% and 4% (compared to the class averages of 18% and 9%). Respondents from cultural landscapes are slightly more likely to be member of class 1 (42%) and less or equally likely in the other classes. Respondents from grass- and farmlands are less likely to be member of Class 1 (34% against 39%) and Class 4 (14% against 16%) and more likely to be member of Class 2 (24% against 19%). Finally, respondents from urban agglomerations are less likely to be member of Class 1 (35% against 39%) and 2 (16% against 19%) and more likely in Classes 3 (21% against 18%), 4 (17% against 16%) and 5 (11% against 9%).

The results are partly in line with our expectations. Forest landscapes and cultural landscapes have high shares of forest and are relatively bio-diverse, with many structural landscape elements. Such landscapes are generally associated with high recreational values. Respondents from these categories are more likely to be member of Class 1 which is characterized by status quo choices and strong opposition against reductions of forest share, increases in corn and changes in field size. This aligns with our expectation of place attachment. The zero willingness to pay for increases of forest indicates diminishing marginal utility. People from forest landscapes are also less likely to be members of Class 3, which is characterized by a strong tendency towards land use changes and cost non-attendance, and of Class 5, which is characterized by low willingness to pay, implying some heterogeneity within this landscape category. About 55% are allocated to Classes 1 and 5 (low willingness to pay), while the remaining share belongs to the other classes which are characterized by high willingness to pay and strong preferences for land-use changes.

Farm- and grasslands are dominated by agriculture and monotonic landscapes with low shares of forest. Respondents from farm- and grasslands are more likely to be members of Class 2, which is characterized by rather large willingness to pay values. This result fits to our expectations of marginal diminishing utility. People living in this landscape have a low endowment of forest, biodiversity and meadows and are thus more willing to pay for an additional unit.

Finally, respondents from urban agglomerations are more likely to be member of Class 3, i.e. are more likely to not attend to costs. While we have no expectation here, this result may be explained by hypothetical bias. The choice scenario is less realistic for people in urban areas and they are less used to the landscapes. They may have ignored the price attribute more often, while at the same time exhibit strong preferences for land use changes. It should be noted that our results indicate preference heterogeneity within landscape categories. We do observe deterministic patterns of distinct preferences between landscape categories. Each landscape category is present in each class with a probability close to the average group probability. Class 1 is the largest class for all landscape catego-

Table 6. Willingness to pay values.

Attribute	Class 1	Class 2	Class 3	Class 4	Class 5
ForMinus10	-52.52***	-165.19***	-	-100.67***	-0.7954
ForPlus10	-5.27	64.33***	-	24.75*	14.24***
FieldHalf	-44.64***	18.77*	-	-75.17***	-16.76***
FieldDouble	-35.34**	-44.83**	-	30.51**	-4.64
Bio85	12.90	32.24**	-	34.75	-5.84
Bio105	7.17	51.32***	-	8.04	12.38**
Corn30	-10.78	23.44	-	2.96	4.50
Corn70	-88.78***	-61.93*	-	-93.47**	-9.80
Mead25	-19.55	41.82**	-	-87.58***	-19.31**
Mead50	-42.09**	3.57	-	-62.74**	-7.53

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Class probabilities by landscape categories.

Landscape	Class 1	Class 2	Class 3	Class 4	Class 5
Forest	0.51	0.19	0.08	0.16	0.04
Cultural	0.42	0.19	0.17	0.14	0.09
Grass/Farm	0.34	0.24	0.19	0.14	0.09
Urban	0.35	0.16	0.21	0.17	0.11
Overall	0.39	0.19	0.18	0.16	0.09

ries and Class 5 is the smallest class for all landscape categories. The effects that we identified should be interpreted as tendencies.

Additional to the latent class analysis, we have estimated separate conditional logit models by landscape categories and used Poe et al. tests (Poe, Giraud, and Loomis 2005) to test for differences in willingness to pay between landscape categories. While exact quantitative results differ, the key findings are similar irrespective of the approach used. The appendix provides more details on the conditional logit models, willingness to pay values and the Poe et al. test results.

5. Conclusion and policy implications

This paper investigated preferences for land-use changes and compared willingness to pay values between different landscape categories in Germany. The data came from a discrete choice experiment inferring preferences for forest share, average size of forest and fields, degree of biodiversity, share of corn and share of meadows within the 15 kilometer radius of the respondents' places of residence. The radius was chosen to represent a typical distance for everyday activities. As the places of residence were geo-referenced, we could combine the data with landscape categories compiled by the German Federal Agency for Nature Conservation. The categories comprised forest landscapes, cultural landscapes, farm- and grassland landscapes and urban agglomerations. The aim of the study was to test whether preferences for land-use changes are correlated with these landscape categories. To do so, we estimated a five-class latent class model and used the landscape categories as explanatory variables in the class membership function. The classes can be distinguished by different willingness to pay values. It turned out that people from forest landscapes and cultural landscapes were less willing to pay for land-use changes and showed a preference towards the status quo situation. Further, people from urban agglomerations and farm- and grassland have high probabilities to be member of classes with large willingness to pay values.

In summary, the results showed that the preferences do differ among landscape categories, but not as systematically as we had expected. Although we find systematic differences in preferences between landscape categories, all landscape categories are relatively evenly distributed across classes. As the latent class analysis has shown, preference heterogeneity exists also within the landscape categories. That is, each respondent, independent of which landscape category the respondent is from, has a probability of at least 8% to be member of any class.

The analysis has implications for policy makers. Our study provides evidence that there are differences in preferences determined by the place of residence. Integrating such differences in landscape planning and cost-benefit analyses may help to improve decisions and induce land-use changes to areas where people appreciate them most or are least reluctant towards a change. A relevant example is the share of corn among agricultural fields. While an increase in the production of energy corn can potentially help to reduce carbon dioxide emissions, it is largely regarded as a disfigurement of the landscape. Our study revealed that opposition to corn is generally large, but stronger in forest and cultural landscapes than in other landscapes. Similarly, increases in forest share should take place in areas with limited forests and near urban agglomerations. Areas characterized by high recreational values such as forest and cultural landscapes should be preserved. Here, people tend more towards the status quo and changes are less appreciated by residents. There is limited interest in increases in forest shares or biodiversity, and at the same time a large resistance against reductions. In contrast, respondents from urban agglomerations and farm- and grasslands are more likely to benefit from increases in forest shares and biodiversity. Here, significant welfare effects of such measures are more likely. Our findings may also be used to inform the design of agri-environmental schemes. For example, compensation may be higher for measures to increase agro-biodiversity in a rather monotonic landscape or near urban areas, because benefits of measures are greater.

Similar studies have investigated land use changes on a broader scale. In their meta-analysis, van Zanten et al. (2014) have found preferences for various landscape elements such as smaller field sizes, but no spatial determinants of preferences. Garrod et al. (2012) have found that preferences for improving ecosystem services depend on the landscape where they are present. This result is in line with our findings, yet our study differs as the proposed land use change always took place at the person's place of residence. In Garrod et al. (2012), this was not the case. To our knowledge, our study is the first study that identifies spatial differentiated preferences for local land use changes.

This study is limited by the fact that we did not investigate the underlying sources for the differences. The landscape categories differ in the status quo of the investigated attributes and in socio-demographic variables. Thus, we are not able to identify the causal effect of living in a certain landscape on preferences. Yet, the study insights provide correlation patterns which are sufficient to foster an understanding of the variation of preferences and willingness to pay between qualitatively different regions.

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Appendix

In order to further investigate differences between landscape categories, we estimate separate conditional logit models for the landscape categories. Table 8 provides the estimation results.

Table 8. Conditional logit models by landscape.

	(1) Forest	(2) Cultural	(3) Farm- and Grasslands	(4) Urban
ASCsq	0.101	0.0171	-0.0959	0.0436
	(0.201)	(0.155)	(0.154)	(0.112)
ForMinus10	-0.647***	-0.594***	-0.532***	-0.458***
	(0.135)	(0.103)	(0.106)	(0.0778)
ForPlus10	0.139	0.284***	0.384***	0.401***
	(0.104)	(0.0789)	(0.0769)	(0.0562)
FieldHalf	-0.152	-0.314***	-0.283***	-0.221***
	(0.119)	(0.0905)	(0.0906)	(0.0670)
FieldDouble	-0.302***	-0.345***	-0.267***	-0.0984*
	(0.107)	(0.0791)	(0.0773)	(0.0561)
Bio85	0.0381	0.129	0.0650	0.204***
	(0.127)	(0.0994)	(0.102)	(0.0753)
Bio105	0.0126	0.246***	0.327***	0.417***
	(0.118)	(0.0884)	(0.0843)	(0.0614)
Corn30	-0.0983	0.176*	0.000266	-0.0231
	(0.125)	(0.0972)	(0.0965)	(0.0706)
Corn70	-0.691***	-0.390***	-0.550***	-0.548***
	(0.127)	(0.0930)	(0.0919)	(0.0670)
Mead25	0.0596	0.0768	-0.131	0.0247
	(0.136)	(0.103)	(0.105)	(0.0761)
Mead50	-0.234*	-0.151	-0.182*	-0.125*
	(0.130)	(0.0939)	(0.0938)	(0.0683)
price	-0.00615***	-0.00755***	-0.00520***	-0.00583***
	(0.00115)	(0.000892)	(0.000858)	(0.000630)
N	5508	8802	8343	15390
pseudo R^2	0.171	0.117	0.087	0.081
AIC	3366.8	5717.0	5604.7	10379.3
BIC	3446.1	5802.0	5689.0	10471.0
χ^2	691.3	753.6	529.8	916.5
Log-Likelihood (NULL)	-2017.1	-3223.3	-3055.2	-5635.9
Log-Likelihood	-1671.4	-2846.5	-2790.3	-5177.6

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All models are highly significant and differences between the landscape categories are visible. In forest landscapes, ForPlus10 is not significant, according to the hypothesis that respondents living in areas with a lot of forests have a limited preference for an increase in the share of forests. An increase in biodiversity to 85 points is only significant in urban agglomerations, where people are characterized by a low degree of biodiversity. Hence, an increase to 85 points has already a positive effect on utility. In the other categories, biodiversity is significant only at the 105 point level. In order to better understand the differences, Table 9 displays the estimated willingness to pay values for the different categories and Figure 3 gives a graphical overview of the willingness to pay values and corresponding 95% confidence intervals. Finally, Table 10 provides the p-values of the Poe test. If the p-value is larger than 0.95 or smaller than 0.05, the willingness to pay values are significantly different. The Poe test has to be interpreted with care. Significant differences will only appear when confidence intervals are small enough. Hence, if the test does not reject the hypotheses that the willingness to pay values are similar, it does not necessarily mean that they are not. It rather means that we cannot show that they are.

Differences in willingness to pay are significant for ForPlus10, Bio105, Corn30 and Corn70. ForPlus10 is not significant for forest landscapes and is significantly higher in open cultural landscapes and urban agglomerations. An increase in biodiversity is valued most in open cultural landscapes and in urban agglomerations and is significantly higher than in forest landscapes. An increase in corn share to 70% has the highest negative willingness to pay in forest landscapes and in open cultural landscapes. There are very few differences between open cultural landscapes and urban agglomerations and no significant differences for Meadows Share and Bio85, which however maybe due to the large confidence intervals. FieldHalf and FieldDouble are nearly always significant, but again, no significant willingness to pay differences exist. Thus, preferences for this attribute are relatively similar.

The results from the Poe test are corresponding to the findings from the latent class analysis. In both exercises, people from open cultural landscapes and urban agglomerations seem to have relatively equal preferences. Similarly, people from forest landscapes and from structurally rich cultural landscapes exhibit similar preferences. The main hypotheses of decreasing marginal utility seem partly confirmed. For example, people in forest landscapes have no willingness to pay for an increase, but a strong willingness to pay against a decrease. However, not in all cases, the results correspond to our expectations.

Table 9. Willingness to pay for different landscape models.

	(1) Forest	(2) Cultural	(3) Farm- and grassland	(4) Urban
ForMinus10	-105.2***	-78.72***	-102.3***	-78.52***
	(29.01)	(16.00)	(26.24)	(15.52)
ForPlus10	22.54	37.66***	73.74***	68.74***
	(16.21)	(10.10)	(16.33)	(10.44)
FieldHalf	-24.75	-41.61***	-54.31***	-37.89***
	(20.69)	(13.79)	(20.61)	(12.65)
FieldDouble	-49.10**	-45.62***	-51.34***	-16.88
	(21.77)	(13.10)	(19.00)	(10.26)
Bio85	6.188	17.10	12.49	34.97***
	(20.38)	(12.77)	(19.15)	(12.37)
Bio105	2.044	32.57***	62.91***	71.57***
	(18.98)	(10.26)	(14.17)	(9.419)
Corn30	-15.98	23.26*	0.0511	-3.970
	(21.72)	(11.95)	(18.54)	(12.29)
Corn70	-112.4***	-51.64***	-105.6***	-93.96***
	(35.27)	(16.03)	(29.91)	(18.47)
Mead25	9.688	10.17	-25.24	4.244
	(21.66)	(13.45)	(21.35)	(12.97)

Standard errors in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 10. Poe test results.

	ForMinus10	ForPlus10	FieldHalf	FieldDouble	Bio85	Bio105	Corn30	Corn70	Mead25	Mead50
Forest vs. Cultural	0.845	0.905	0.251	0.481	0.879	0.987	0.992	0.965	0.696	0.558
Forest vs. Farm	0.412	0.998	0.174	0.529	0.644	0.993	0.805	0.589	0.327	0.517
Forest vs. Urban	0.795	0.997	0.318	0.711	0.877	1.000	0.837	0.683	0.675	0.492
Cultural vs. Farm	0.074	0.986	0.33	0.55	0.185	0.775	0.056	0.046	0.14	0.449
Cultural vs. Urban	0.4	0.975	0.597	0.779	0.486	0.908	0.025	0.041	0.474	0.403
Farm vs. Urban	0.889	0.321	0.733	0.683	0.802	0.623	0.505	0.587	0.867	0.458

Figure 3. Willingness to pay confidence intervals by sample.