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Assessing spatial preference heterogeneity in a mixed-use landscape

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ABSTRACT

Discrete choice experiments are playing an increasingly important role in environmental valuation given their potential to characterize the implicit tradeoffs that stakeholders are willing to make among competing future conditions. Yet, most choice models focus on specific populations and policy issues rather than examining landscape-level preferences across regional spatial scales. We investigated the spatial heterogeneity of public preferences across an American Midwestern county using data from interviews, focus groups, and a mixed-mode household survey that included a discrete choice experiment. This study generated geo-located individual-specific parameter estimates to determine how a suite of land use and economic attributes were driving residents' visions for the future of Will County, IL, including residential growth, protected grasslands, recreation, agriculture, bison reintroduction, and unemployment rates. Global and local spatial autocorrelation patterns were used to examine the landscape preferences expressed by individual respondents in relation to their neighbors. Results showed that preferences within the sample were heterogeneous across all model attributes. Local spatial autocorrelation findings also revealed local clustering of high to low preferences that was particularly pronounced for agriculture and residential growth. We provide insight on how location of residence relates to stakeholder preferences for landscape attributes to guide planning and management agencies faced with the allocation of scarce resources on the rural-urban fringe.

1. Introduction

Individual preferences for the material and non-material benefits of places are complex and fundamentally important for environmental decision-making around multi-functional landscapes (Boxall & Adamowicz, 2002; Díaz et al., 2020; Muhar et al., 2018; Plieninger et al., 2013). Given that preferences are shaped by landscape conditions that range from local to global scales (Bockstael, 1996; Schläpfer & Hanley, 2003; Zube, Sell, & Taylor, 1982), researchers are challenged to account for how preferences vary across space and time, especially in settings that include multiple land use types and diverse socio-economic conditions (Dissanayake & Ando, 2014; Schläpfer & Hanley, 2003). In recent years, discrete choice experiments (DCE) have been used to capture spatial preference heterogeneity (Bateman et al., 2002; Wang & Swallow, 2016); however, most DCE research has underutilized the role spatial processes play in understanding individuals' stated preferences (Bockstael, 1996; Glenk et al., 2020). A deeper understanding of how preferences for landscape conditions are spatially distributed can advance theoretical expectations for detected valuation patterns, while focusing policy to align with localized public opinions that emerge from the relationship between people and their environments (Campbell et al., 2008; Czajkowski et al., 2017; Glenk et al., 2020; Schläpfer & Hanley, 2003).

Discrete choice modeling is a well-established technique for examining individual preferences for future growth scenarios and providing insights on tradeoffs made among competing attributes (Louviere et al., 2000). This technique was originally developed by economists to model how people made decisions about multi-attribute goods and services in transportation and marketing applications (McFadden, 1986; Louviere & Hensher, 1982). Discrete choice experiments have now been implemented across a wide range of fields including health care policy (Ryan & Gerard, 2003; Soekhai et al., 2019), recreation (Hunt, 2005; van Riper et al., 2011), planning (Arnberger & Eder, 2011), and environmental and resource economics (Adamowicz et al., 1994; Campbell et al., 2009; Dissanayake & Ando, 2014). Typically, individuals are presented with hypothetical scenarios and asked to provide a discrete choice that enables researchers to infer the relative importance of attributes. Recent advances in the environmental valuation literature have focused on understanding differences in individual preferences, known as 'preference heterogeneity,' to identify sources of variation within a sample

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(Hensher & Greene, 2003; Sagebiel et al., 2017; Train, 1998). Although previous researchers have effectively modeled preference heterogeneity (Arnberger & Eder, 2011; Sayadi et al., 2009; van Riper et al., 2011), less attention has been focused on *spatial* heterogeneity in preferences (Bateman et al., 2002; Campbell et al., 2008). This gap is problematic because assumptions of homogeneity overlook the important role of local conditions in shaping viewpoints (Bockstael, 1996; Schläpfer & Hanley, 2003; Stedman, 2003). In other words, DCEs that incorporate spatial relationships can reveal localized patterns that are otherwise invisible (Johnston & Ramachandran, 2014; Meyerhoff, 2013) and uncover local clusters of high (or low) preferences within spatial units such as municipalities or counties.

A range of techniques have been used to account for spatial heterogeneity in DCEs to reveal how individual decisions vary across spatial scales. A body of work has incorporated spatial variables using interaction terms to better understand preferences as a function of distance to assets such as recreation sites (Louviere & Timmermans, 1990; Schaafsma et al., 2012), restored grasslands (Dissanayake & Ando, 2014), and wetlands (Bateman et al., 2006). Using this method, scholars have demonstrated the importance of 'distance decay' to describe how preferences decrease with increases in distance (Brouwer et al., 2010; Glenk et al., 2020; Marchment & Gill, 2019; Vandeviver et al., 2015). Similarly, scholars have demonstrated that people tend to place more value on conditions in closer proximity to their place of residence (Brouwer et al., 2010). Distance has also been related to willingness-to-pay (WTP) to determine the amount that an individual would pay for a public good or service as distance to the good increases (Hanemann, 1991). Bateman et al. (2006), for example, found significant distance-decay in respondents' willingness-to-pay for preserving wetlands and improving river conditions in two case studies. While spatial interaction terms in DCEs can provide valuable information on how preferences vary across space, generating these aggregate effects for an entire study area does not explicitly reveal how preferences exhibit patchiness or clustering patterns (Campbell et al., 2008; Schaafsma et al., 2012).

Knowledge of preferences at the individual-level, rather than in aggregate, has paved the way to an expanding literature in spatial econometrics (Abildtrup et al., 2013; Campbell et al, 2008, 2009; Czajkowski et al., 2017; Glenk et al., 2020; Johnston et al., 2015; Johnston & Ramachandran, 2014; Meyerhoff, 2013; Vollmer et al., 2016; Yao et al., 2014). Researchers have utilized individual-specific outputs from logit models in various posterior analyses to capture preference heterogeneity (Train, 1998). For example, individual-specific parameter estimates have been used in second-stage regression analyses to understand how spatially-defined variables (e.g., population density, presence of a water body) contribute to preferences (Abildtrup et al., 2013; Czajkowski et al., 2017; Yao et al., 2014) and in exploratory spatial analyses testing the spatial dependence of preferences (Campbell et al., 2008, 2009; Johnston et al., 2015; Johnston & Ramachandran, 2014; Meyerhoff, 2013). The latter collection of studies has provided insight on how individual preferences, based on location of residence, vary across space. Campbell et al. (2008), in particular, assessed how preferences for landscape improvements were distributed in Ireland and demonstrated spatial dependence by showing that preferences of individuals living in close proximity were more similar than people that lived far apart. Using similar methods, Meyerhoff (2013) assessed willingness-to-pay (WTP) for alternatives to wind energy and found lower WTP values were clustered in urban areas. Testing the spatial dependence of preferences has been done in a variety of contexts including agricultural lands (Wang & Swallow, 2016), protected forests (Abildtrup et al., 2013), and grasslands (Dissanayake & Ando, 2014). However, few have accounted for preferences across a variety of public and private land use types despite the relevance of this research approach for regional planners, land use managers, and public officials who make decisions that span jurisdictional boundaries.

The purpose of this study was to analyze preferences for land use and economic conditions in an American Midwestern county that has been historically dominated by agriculture but increasingly accommodates other competing interests across public and private sectors (Foelske et al., 2019). We aimed to understand how preferences for these conditions vary across space. Specifically, how did individual preferences for growth scenarios vary based on residential location? In this paper, we identified spatial regional trends, local outliers of preferences, and the locations where preferences were particularly high (or low). Given the county's diverse landscape, we hypothesized that individuals living in close proximity would be more similar than those living further away (Tobler's first law of geography; Tobler, 1970), and that preferences would exhibit local clustering. Therefore, three objectives directed this study: 1) estimate residents' preferences for county-wide landscape characteristics (referred to herein as "attributes"); 2) assess the spatial dependence of individual preferences; and 3) analyze and map the local spatial patterns of preferences for the model attributes.

This article advanced the environment and planning literature in multiple ways. We illustrated heterogeneity in preferences for future landscape scenarios by drawing from both qualitative and quantitative data to identify meaningful outcomes for decision-makers working in mixed land-use contexts. Using a random parameters logit model as well as global and local spatial autocorrelation tests, we extended previous work by exploring spatial heterogeneity in a posterior test that analyzed the spatial dependence of individuals' preferences. This is one of few studies (exceptions include: Johnston et al., 2015; Johnston & Ramachandran, 2014; Meyerhoff, 2013) to test both global and local spatial autocorrelation using data from a DCE, and to the authors' knowledge, this is the first study to use these methods in the context of regional planning on the rural-urban fringe.

2. Methods

2.1. Study site

This study was conducted in Will County, Illinois, which is situated within the Chicago Metropolitan Statistical Area and is the state's fourth most populous county (see Fig. 1; "Will County, IL," 2018). This site is a mixed-use landscape; it is a productive agricultural region, transportation hub, economic engine, and place for recreation and conservation activities that are valued by the local community (Strauser et al., 2018). A majority of the county's population and opportunities for employment are located in the northern region while the south is largely characterized by agrarian land use practices (Chicoine, 1981). In 2012, farms occupied approximately 43% of Will County and were mostly dedicated to growing field corn, followed by soybeans and foraging crops such as hay ("2012 State and County Profiles, 2018"). Due to its close proximity to Chicago and central location in the Midwestern US, Will County is an important transportation center. The county is at the forefront of the transportation industry as it boasts multiple interstate systems, well-developed rail lines, a national intermodal transportation facility, and an active river route (Evans et al., 2018). Additionally, there have been ongoing conversations among policymakers for several decades about developing a new interstate system and major airport in the county that would stimulate employment opportunities. However, these developments have experienced opposition, primarily from rural residents that are skeptical of the benefits for local communities (Dolan, 2018; Steele, 2016).

Amidst the residential areas and industry presence, there is a patchwork of protected areas that exist in Will County. The largest green space is Midewin National Tallgrass Prairie, which encompasses over 72 square kilometers in the southwest region of the county. Managed by the US Forest Service since 1996, the protected area embodies the idea of 'multiple-use and sustained yield' (Multiple Use Sustained-Yield Act of 1960). Midewin contains recreational trails, a restored tallgrass prairie system, existing infrastructure from the land's previous use as a federal arsenal, and a bison herd on 1200 acres of the prairie. Bison were

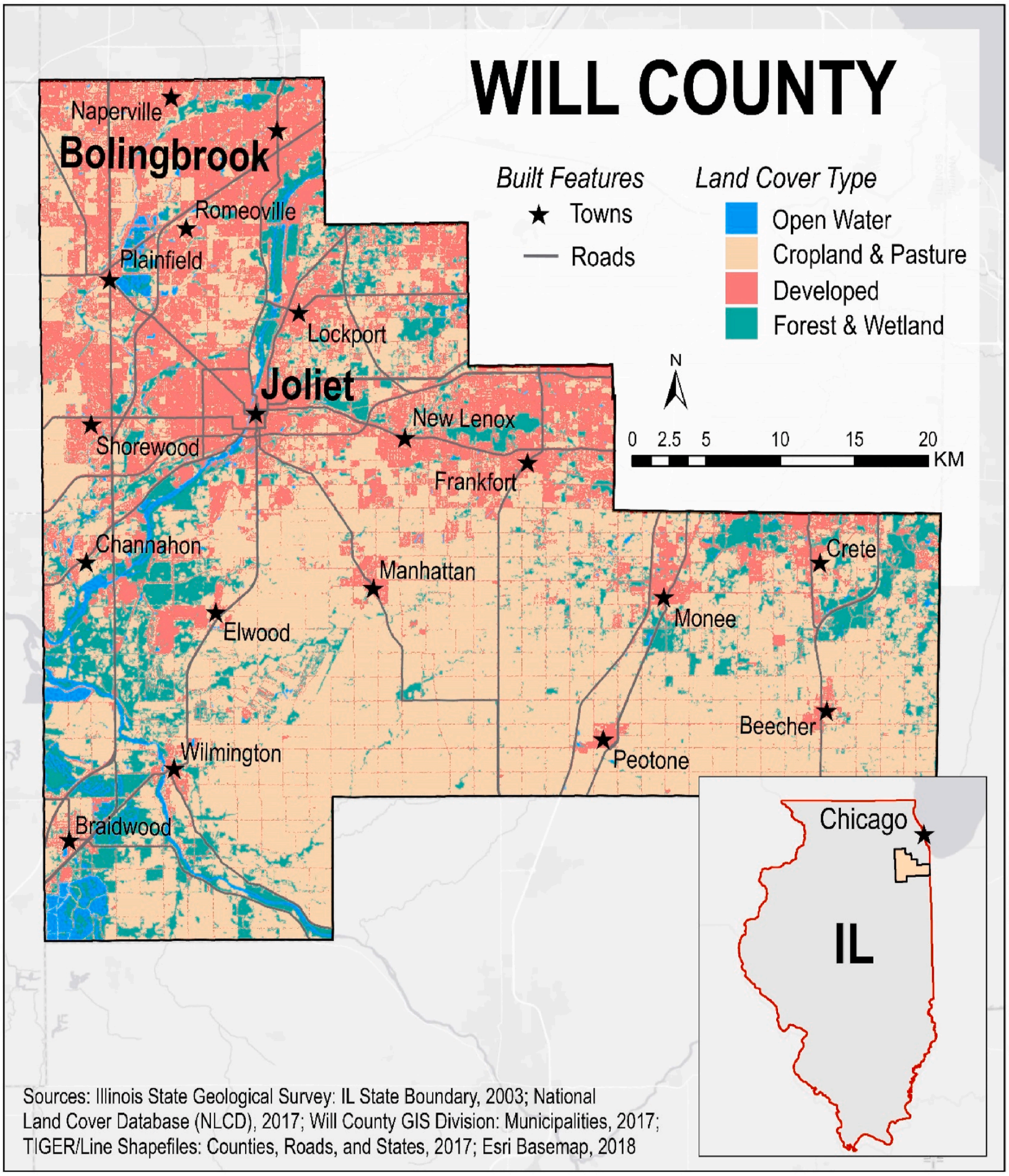

Fig. 1. Land cover in Will County, Illinois.

reintroduced in 2015 and increased visitation threefold after one year of their arrival (Lafferty, 2016). In addition to Midewin, the Will County Forest Preserve District manages over 21,000 acres with one-third of the land in active restoration in the county ("Land Management," 2017). This area also has an extensive trail system that includes the historic Illinois and Michigan (I&M) Canal Trail and the 23-mile long Wauponsee Glacial Trail. These features serve important roles in providing recreational opportunities and advancing conservation initiatives as the county continues to grow.

2.2. Discrete choice experiment

The design of our discrete choice experiment (DCE) was informed by preliminary qualitative research (Coast & Horrocks, 2007). This stage of the study enabled us to identify attributes relevant to future growth scenarios within Will County. We conducted an in-depth assessment of stakeholder groups involving semi-structured interviews (n = 10) and a focus group held with experts in Will County (n = 8) over an 18-month period (Strauser et al., 2018). After collecting these qualitative data, we chose six attributes to be included in our choice experiment: *Residential Growth, Protected Grasslands, Distance to Recreation Areas, Agriculture, Bison Presence,* and *Unemployment Rates*. Each attribute included three or five levels (see Table 1). The levels were set to represent a range of conditions that residents could encounter in the study area and were used to gauge the strength of preferences for each attribute (or the degree to which individuals were 'willing-to-accept' undesirable attributes such as unemployment). Generally, the levels spanned a gradient ranging from slower growth than what was being experienced at the time this research was conducted to faster growth that could be experienced in the future. Although we consulted local leaders involved in policy-making for feedback on our attributes, the scenarios developed for our choice experiment were purely hypothetical in nature. In line with previous research, we developed these scenarios using NGene 1.1.2 software (Arlinghaus et al., 2014; Greiner et al., 2014; Wang & Swallow, 2016). Using Bayesian priors, we optimized the design for the multinomial logit model (MNL) but evaluated the design only for the random

Table 1
Choice model attributes and levels for the survey instrument.

Attribute	Description	Levels
1 Residential Growth	The annual population growth in the county	2% decrease No growth 2% increase 4% increase 6% increase
2 Projected Grasslands	The percent change of county land designated as protected grasslands	No change 5% increase 10% increase
3 Distance to Recreation Areas	The distance to the nearest recreation area from the resident's home	20 miles 7 miles 1 mile
4 Agriculture	The percentage of land in the county used for agricultural production	30% land 50% land 70% land
5 Bison Presence	The percent change in total number of bison in the county	No change 3% increase 5% increase
6 Unemployment Rates	The percentage of people unemployed in the county	2% unemployed 4% unemployed 8% unemployed

parameters logit (PRL) model (Greiner et al., 2014). We used Gaussian draws with 531,441 draws per repetition and 1000 repetitions (Bliemer et al., 2008).

Following the development of our DCE, we took steps to refine our questionnaire before survey administration. We pilot tested the survey at a county fair in Summer 2017 (n = 120) to ensure the attributes and levels chosen were realistic and meaningful to potential respondents. The pilot test results also generated fixed priors based on a multinomial logit model. These priors were in turn used to create an efficient experimental design of the choice sets (Campbell et al., 2009; Dissanayake & Ando, 2014; Garrod et al., 2012; Greiner et al., 2014). Our final choice design had a 99.6% D-efficiency and included 18 choice questions, blocked into two different survey versions. Our sample was identified using a random address-based sampling approach and surveyed using an adaption of the 'Tailored Design Method' (Dillman et al., 2014). The survey questionnaire was preceded by an introductory letter sent to residents. The introductory letter provided to potential respondents was endorsed by a local organization called The Conservation Foundation. This form of sponsorship was secured to boost our response rate due to enhanced credibility with local residents (Dillman et al., 2014). Surveys were sent to 1500 addresses in Will County in Spring 2018. The mixed mode (mail-back or online) survey was administered to respondents tasked with choosing their preferred scenario among two experimentally designed options and an 'opt-out' option (see Fig. 2).

A discrete choice experiment is a tool used to elicit preferences from individuals about multi-attribute options. Choice experiments are guided by random utility theory which assumes that individuals under identical conditions make different choices to maximize personal benefits (Thurstone, 1927). Multinomial logit (MNL) models have been used most often to capture stated choices (Brouwer et al., 2010; Louviere et al., 2000), though an increasing number of studies have adopted more flexible models such as the random parameters logit (RPL) model (Brouwer et al., 2010; Hensher & Greene, 2003; Hunt, 2005). The RPL model is preferred to traditional approaches because it accounts for heterogeneity across individual preferences and operates under less restrictive assumptions (Bliemer & Rose, 2013; Campbell et al., 2009; Hensher & Greene, 2003; Train, 1998). Specifically, the RPL model allows attribute effects to vary across a sample of respondents and accommodates a more complex error term where uncertainty in the model can be correlated across attributes and choice sets (Bliemer & Rose,

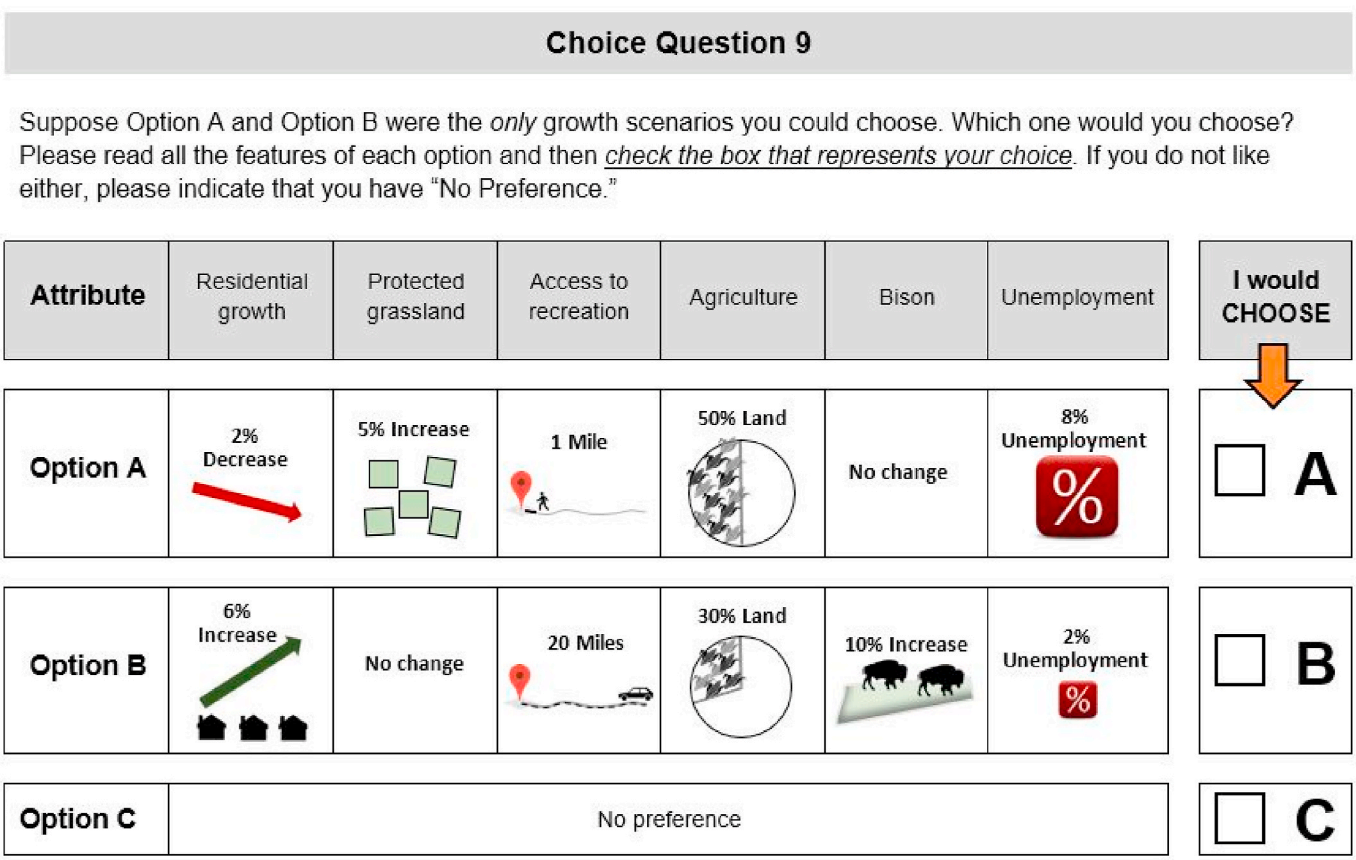

Fig. 2. Example choice question from the survey.

2013). Because individuals have different tastes and preferences, not accounting for heterogeneity in a choice model can lead to biased results (Boxall & Adamowicz, 2002). In allowing parameters to vary across individuals, each random parameter has a distribution with mean and standard deviation values (Hensher & Greene, 2003). A random parameters logit model was employed in the present study to analyze the choice dataset using NLogit 6 software. Choice, the dependent variable, was dummy coded (0, 1) to delineate if respondents chose experimentally-designed alternatives A or B or the no-preference alternative C. All study attributes were specified as random and followed normal distributions (Johnston & Ramachandran, 2014; Sagebiel et al., 2017), and the third alternative was represented by a constant.

The RPL model was employed in this study because of its ability to account for heterogeneity in preferences and to estimate individual-specific parameters. Individual-specific parameters were generated for each person in the sample and were based upon the mean parameter of a subgroup of individuals that chose the same option when faced with the same choice set (Hensher et al., 2005; Train, 2009; Vollmer et al., 2016). These estimates were conditional on individuals' known choices and became increasingly accurate with a larger number of choice questions (Johnston et al., 2015). Empirically, individual-specific parameters from RPL models are used to understand the shape of a parameter distribution or to conduct posterior tests (Scarpa et al., 2005; Vollmer et al., 2016). Using the latter approach, we derived individual-specific parameters for all six attributes to test for spatial dependence of landscape preferences. Parameters were then mapped using ArcMap 10.6 software based on geocoded respondent addresses (Johnston et al., 2016; Meyerhoff, 2013).

2.3. Global and local spatial autocorrelation

Spatial autocorrelation methods were used to assess variation in landscape preferences at the household level. In line with previous research (e.g., Campbell et al., 2008; Johnston & Ramachandran, 2014), we did not explain spatial variation in preferences, rather, we evaluated preferences in a univariate exploratory analysis. In this study, we used both global and local methods to identify spatial clustering and dispersion of individual-specific parameters. Global methods were applied across the study area while local methods depicted trends around each observation in space (Fotheringham & Brunsdon, 2010). We used univariate Moran's I and Gi* analysis to analyze global and local spatial autocorrelation, respectively. Global Moran's I was the correlation of a value at location n and its neighboring values. A Moran's I value above zero indicated positive spatial autocorrelation in which similar values were clustered together while a value below zero specified negative autocorrelation where nearby locations had dissimilar values (Campbell et al., 2008; Haining, 2003).

In addition to analyzing global spatial autocorrelation of the individual-specific parameters, local trends were analyzed. Gi*, a common indicator of local spatial autocorrelation, was used to identify clusters of significantly low and high preferences (Getis & Ord, 1992). In this analysis, the average value for clusters of observations, that is, observation n and its neighbors, was compared to the global average. Significant clusters existed if the local average was significantly different from the overall sample (Johnston & Ramachandran, 2014). Both spatial autocorrelation tests were completed using GeoDa spatial software (Anselin et al., 2006). Local 'neighbors' were defined using a spatial weights matrix, known as the 'spatial lag.' A queen contiguity first-order spatial weights matrix was used for the spatial analyses in this study. Using this matrix, neighboring individuals were defined by those that shared a border or vertex with individual i. Monte Carlo methods were used for significance testing to determine if the spatial distribution of preferences was significantly different from random. The Monte Carlo inference process randomly re-assigned the values (i.e., individual-specific parameters) among the points (i.e., respondent households). This process was repeated 99,999 times to create a reference distribution, and the actual Moran's I and Gi* values were compared with the reference distributions to understand how different the spatial dependence of preferences was from random. These values were generated for each of the six landscape attributes.

3. Results

Our approach to random address-based sampling yielded 440 survey responses (30.6% response rate) from residents in Will County, Illinois. Of those surveys, 386 were used in our analysis after removing incomplete data (n = 37) and 'protest votes' (n = 17) in response to our discrete choice experiment (Greiner et al., 2014). Eighty percent of respondents returned a mail-back version of the survey compared to 20% who chose the online option. Upon geocoding the respondents' address locations, we found the majority of respondents were from the northern part of the county but lived in different environments. Respondents' residential locations corresponded with a variety of land cover types (see Table 2), with the majority living on low- or medium-intensity developed land. According to the National Land Cover Database (2011), these areas have a mixture of constructed materials and vegetation with impervious surfaces accounting for 20–49% of the total cover in low intensity regions and 50–79% in medium intensity regions.

Background information on respondents was collected to better understand Will County residents. The mean age was 56.2 years (SD = 14.7; SE = 0.75), ranging from 18 to 93 years old. The average household size was two adults (SD = 0.8; SE = 0.04) and one child (SD = 1.3; SE = 0.08). A slight majority of respondents identified as female (53.5%) and the majority racially identified as White (83.2%). Seventy-three percent of respondents reported having completed at least some college, and the largest group reported their yearly household income before taxes was $50,000-$99,999. On average, respondents had lived in their current home for 16.7 years (SD = 13.08; SE = 0.65) and in Will County for 19.3 years (SD = 18.36; SE = 0.97). The majority stated they were currently employed (65.8%) with education being the most common employment sector (20.2%). On the first page of the survey questionnaire, respondents were asked about their knowledge on the attributes used in the choice model using a five-point Likert scale ranging from 1 (no knowledge) to 5 (high knowledge). Overall, knowledge of the attributes in Will County was low, but respondents reported highest levels of knowledge on residential growth (M = 2.3; SD = 1.31; SE = 0.06), followed by recreation and tourism (M = 2.2; SD = 1.21; SE = 0.06) and protected grasslands (M = 2.0; SD = 1.11; SE = 0.05).

3.1. Preferences for landscape scenarios

In line with Objective 1, we employed a random parameters model and observed a range of landscape preferences in Will County, IL (see Table 3). Results from the DCE were generated from 3421 choice set

Table 2
Respondent residential locations and land cover type (N = 386).

Land cover type[a]	Number of People Living within the Landcover Type	Percentage
Developed, Open Space	13	3.4
Developed, Low Intensity	197	51.0
Developed, Medium Intensity	154	39.9
Developed, High Intensity	10	2.6
Deciduous Forest	1	0.3
Mixed Forest	1	0.3
Herbaceous	3	0.8
Cultivated Crops	4	1.0
Woody Wetlands	3	0.8

[a] National Land Cover Database (2011).

Table 3
The mean and spread of the six random parameters from the random parameters logit model, including coefficients, standard deviations, and standard errors (SE) (N = 386).

Attributes	Coefficients (SE)	Std. Deviation (SE)
Residential Growth	−0.031[b] (0.013)	0.181[a] (0.017)
Protected Grasslands	0.035[b] (0.015)	0.059[b] (0.027)
Distance to Recreation Areas	−0.072[a] (0.005)	0.060[a] (0.007)
Agriculture	0.023[a] (0.003)	0.029[a] (0.003)
Bison Presence	0.013[c] (0.007)	0.028[c] (0.015)
Unemployment Rates	−0.374[a] (0.023)	0.250[a] (0.025)
Constant	−3.762[a] (0.245)	2.883[a] (0.200)

Log-likelihood = −2609; Akaike information criterion (AIC) = 5246; No. of observations = 3421; Pseudo R^2 = 0.306.
[a] = $p < 0.0001$.
[b] = $p < 0.05$.
[c] = $p < 0.10$.

observations, and the McFadden's pseudo R^2 value of 0.306 indicated a good fitting model (Hensher & Johnson, 1981). Coefficients of all six attributes in the model were significantly different from zero ($p < 0.10$) and had varying effects on the dependent variable of "choice." Respondent choices were negatively driven by higher *Residential Growth* and *Unemployment Rates* while increases in *Protected Grasslands*, shorter *Distances to Recreation Areas*, more land in *Agriculture*, and greater *Bison Presence* increased the likelihood of a respondent choosing a given scenario. The model attributes also exhibited significant standard deviations of the random parameter distributions, indicating that preference heterogeneity existed among all parameters. Interactions between the attributes were tested, and the correlation between *Bison Presence* and *Protected Grasslands* was significant (Appendix A). Interactions between the model attributes and socio-demographic characteristics (e.g., gender and age) are presented in Appendix B, showing that these relationships were not strong.

3.2. Spatial dependence of preferences

To understand the preference heterogeneity that existed among individuals in Will County, we spatially located individual-specific parameter values based on respondents' location of residence, as articulated in Objective 2. A global spatial autocorrelation assessment of the geocoded parameters revealed overall spatial dependence for each attribute (see Table 4). Based on the Moran's *I* statistics of individual preferences, there was a low degree of spatial dependence among the parameters. Further, patterns of spatial dependence neither trended towards positive or negative spatial autocorrelation. Only the *Distance to Recreation Areas* attribute had a statistically significant trend ($p < 0.01$), exhibiting negative spatial autocorrelation. That is, preferences for recreation were dissimilar among nearby households. Individuals with high and low preferences for how far to travel to engage in recreation activities tended to be located near one another.

Table 4
Global Moran's *I* statistics, z-values, and p-values for preferences of the six attributes (N = 386).

Attributes	Moran's I	z-value	p-value
Residential Growth	0.004	0.2164	0.408
Protected Grasslands	−0.032	−0.9912	0.160
Distance to Recreation Areas	−0.072	−2.283	0.009
Agriculture	0.043	1.515	0.068
Bison Presence	−0.004	−0.056	0.485
Unemployment Rates	0.009	0.386	0.342

Note: Significance testing with 99,999 permutations; spatial weights defined using queens contiguity (first order).

3.3. Local patterns of preferences

In line with Objective 3, we analyzed landscape preferences using local spatial autocorrelation tests to identify clusters of significantly high (or low) preferences. The number of local cluster types is reported in Table 5 for each of the six landscape attributes. Significant high-high clusters (or hotspots) and low-low clusters (or coldspots) existed for all attributes although the majority of respondents did not show significant clustering with neighboring individuals for all attributes. High-high clusters identified where an individual with high preferences surrounded by neighboring high preferences existed, and low-low clusters were locations where an individual with low preferences was surrounded by neighboring low preferences. Thus, individual preferences were similar to neighboring individuals in specific areas of the county. Preferences for *Agriculture* resulted in the most significant local clusters (n = 56), followed by *Residential Growth* clusters (n = 52).

The local spatial autocorrelation tests illustrated spatial clustering of landscape preferences across Will County (see Fig. 3). The most prominent spatial clustering existed for the *Agriculture* attribute (see Fig. 3d). Spatial clustering of the *Residential Growth* attribute also followed clear patterns within the county (see Fig. 3a). Distinct bands of hotspots and coldspots emerged with a cluster of contiguous hotspots to the northwest of the city of Joliet and another hotspot band located in the center of the county. Coldspots for *Residential Growth* were located primarily in a band extending northeast from Joliet and another in the southeast region of the county. Spatial clustering of preferences for the other attributes existed, but regional trends were less apparent. For example, preferences for *Distance to Recreation Areas* were mixed in the far northern part of Will County, but a cluster of hotspots emerged in the central region (see Fig. 3c). Spatial patterns for the conservation-related attributes, *Protected Grasslands* (see Fig. 3b) and *Bison Presence* (see Fig. 3e), were also mixed with less evident clustering of hotspots and coldspots. Finally, clusters of preferences for lower *Unemployment Rates* surrounded the greater Joilet region while clusters of 'willingness to accept' higher *Unemployment Rates* existed in the central region of the county and in the northwest corner west of Bolingbrook (see Fig. 3f).

4. Discussion

This study advanced knowledge of the spatial patterns of landscape preferences across a regional scale on the rural-urban fringe. Results from a discrete choice experiment paired with spatial autocorrelation methods illustrated how preferences for future growth varied across Will County, IL. First, the choice experiment we conducted using a random parameters logit (RPL) model indicated that all model attributes were significant predictors of choices for future growth scenarios. We observed that Will County residents were more likely to choose scenarios with more land in *Agriculture*, more *Protected Grasslands*, greater *Bison Presence*, and closer *Distance to Recreation Areas* but less likely to

Table 5
Local clusters of landscape preferences.

Attributes	High-High Clusters n (%)	Low-Low Clusters n (%)	Non-Significant n (%)
Residential Growth	27 (7.0%)	25 (6.5%)	334 (86.5%)
Protected Grasslands	23 (6.0%)	21 (5.4%)	342 (88.6%)
Distance to Recreation Areas[a]	13 (3.4%)	14 (3.6%)	359 (93.0%)
Agriculture	31 (8.0%)	25 (6.5%)	330 (85.5%)
Bison Presence	15 (3.9%)	16 (4.1%)	355 (92.0%)
Unemployment Rates	20 (5.2%)	19 (4.9%)	347 (89.9%)

Note: Clusters are significant at $p < 0.05$; spatial weights defined using queens contiguity (first order).
[a] Reverse-coded attribute so that high-high clusters represented preference for closer recreation areas.

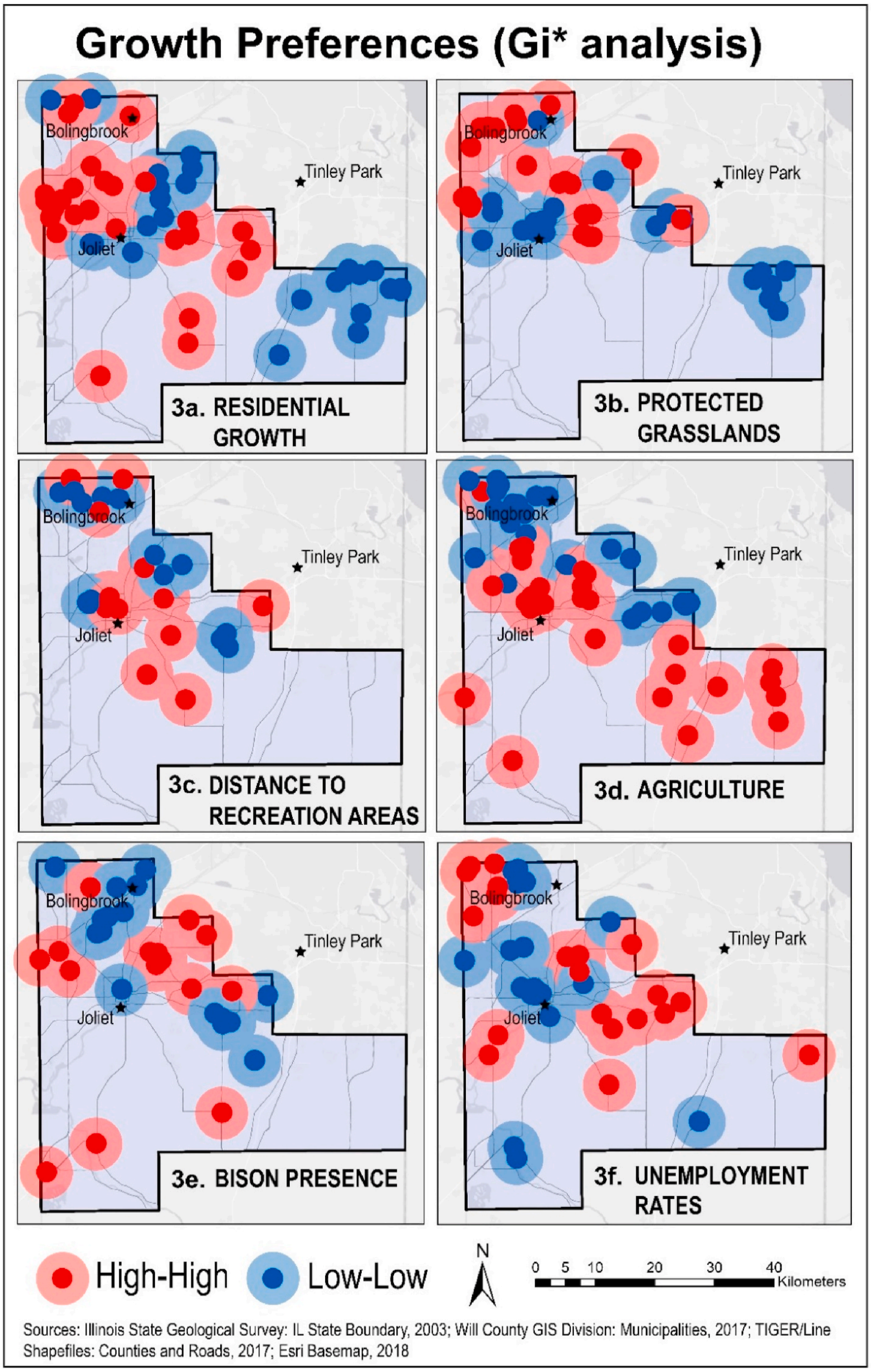

Fig. 3. Growth preferences illustrated from a Gi* hotspot analysis (99,999 permutations; queens contiguity with first order effects). Results are shown for Residential Growth (3a), Distance to Recreation Areas (3b), Bison Presence (3c), Protected Grasslands (3d), Agriculture (3e) and Unemployment Rates (3f). The Distance to Recreation attribute values were reverse-coded such that high-high clusters represented preference for closer recreation areas.

choose scenarios with greater *Residential Growth* and higher *Unemployment Rates*. These findings align with previous research conducted in the American Midwest that has suggested open space protection, grassland restoration, and preservation of agricultural lands are preferred by stakeholders (Dissanayake & Ando, 2014; Slemp et al., 2012). The RPL model enabled us to account for significant preference heterogeneity in all six attributes, indicating that their impact on choice was not the same across individuals. Though the mean coefficients of *Protected Grasslands, Distance to Recreation Areas, Agriculture,* and *Bison Presence* indicated a desire for more of these 'public goods' in the future, stakeholder preferences for these attributes were significantly different across individuals. Likewise, the mean coefficients for *Residential Growth* and *Unemployment Rates* were negative, but this trend did not describe the preferences held by all individuals in the sample.

This research provided insight on the challenges and limitations of conducting choice experiments. First, we found that collecting preliminary qualitative data and pilot testing the choice experiment was integral for developing a relevant and meaningful survey instrument

(Coast & Horrocks, 2007). We suggest researchers prioritize these initial stages of research when creating a choice experiment. Second, in the survey questionnaire, we did not include questions that prompted respondents to reflect on the process of participating in the choice experiment. As indicated in previous research (Greiner et al., 2014), the inclusion of follow-up questions can provide reasoning for cases of 'attribute non-attendance' (i.e., specific attributes that are ignored or simply not considered by respondents when making a choice) or 'protest-responses' (i.e., respondents who do not agree with the context of the scenarios and as a result always choose only the opt-out option). Lastly, because of the hypothetical nature of choice experiments, respondents' stated preferences may differ from actual behavior. Thus, choice experiments should reflect, as close as possible, actual choice contexts (Hoyos, 2010). We recognize that our DCE could have been strengthened to reduce ambiguity and improve the reliability and validity of the experiment. The 'no-preference' option, for example, presented interpretation difficulties and could have been clarified by using reference attributes and levels (Rose et al., 2008). Further, we did not establish a time-period in which the growth scenarios could have hypothetically occurred. Evaluating the growth scenarios within an established time frame (i.e., growth within the next 10 years) would have improved the comprehensibility of the choice experiment.

In the second stage of our analysis, spatial autocorrelation methods illustrated spatial heterogeneity in individual preferences for the choice experiment attributes. Our results underlined the importance of considering localized spatial patterns of preferences for future growth given that global spatial autocorrelation tests showed little evidence of overall spatial dependence in individual preferences. Global spatial autocorrelation indicated that overall spatial dependence of the six attributes was weak. This finding extends other studies that have reported on results from global spatial autocorrelation of individual-specific parameters (Johnston et al., 2015; Johnston & Ramachandran, 2014; Meyerhoff, 2013). Although the Moran's I values for *Distance to Recreation Areas* and *Agriculture* preferences were significant at the 90% confidence level, both values were within 0.10 from zero, indicating relatively weak autocorrelation given that values above 0.30 or below −0.30 represent strong autocorrelation patterns (O'Sullivan & Unwin, 2014). Weak global clustering might have been linked to the spatial resolution of individual households as the units of observation. At this scale, global patterns did not demonstrate a strong relationship between the preferences of individuals and their neighbors, as defined by the spatial weights matrix. It could be that patterns existed at a different spatial scale. Previous research has indicated that aggregating preferences across spatial units (e.g., census blocks, electoral districts) has had a stronger influence on global spatial dependence (Campbell et al., 2009; Czajkowski et al., 2017). However, in line with Johnston et al. (2015), Johnston and Ramachandran (2014), Meyerhoff (2013), and Vandeviver et al. (2015), we chose individual households as the unit of analysis to not mask local variability in preferences and to avoid aggregation bias. Future research should carefully consider the unit of analysis for understanding autocorrelation patterns of preferences.

Though the study attributes did not exhibit strong global spatial autocorrelation patterns, significant local patterns were detected. Local spatial autocorrelation methods illuminated the locations where preferences were clustered within the county. The majority of local clusters were non-significant for all six attributes. In other words, preferences of individuals across Will County generally did not strongly relate with the preferences of neighboring individuals. However, in specific places within the county, preferences of individuals and their neighbors were very similar. Fig. 3 showed the locations where local spatial autocorrelation was significant across the six attributes. The *Residential Growth* and *Agriculture* attributes exhibited the most spatial clustering with high and low preferences for these attributes clustering in distinct areas across the county. Hotspots of preferences for *Agriculture* (see Fig. 3d), for example, coincided with the southern region of the county where the landscape was dominated by cropland. Agricultural coldspots – clusters of low preference – were found only in the northern half of the county. This finding may be explained by the idea of 'locational sorting' where individuals move to a location because they prefer the amenities it provides (Abildtrup et al., 2013; Chatman, 2009). Further, shared experiences in regards to an agrarian lifestyle may have been a factor in shaping the preferences of neighboring individuals (Glenk et al., 2020). The literature also suggests that preferences for a resource are higher when that resource is more abundant because of increased familiarity (Dissanayake & Ando, 2014).

This study identified several opportunities for future research to analyze individual preferences using spatial autocorrelation methods. First, our assessment of both global and local spatial dependence of preferences identified distributional patterns but did not explain why these patterns occurred. Other methods such as spatial regression (Abildtrup et al., 2013; Czajkowski et al., 2017; Lee et al., 2017) and latent class analysis (Scarpa et al., 2005) can be used in tandem with spatial autocorrelation for future studies to better understand the factors that influence the spatial distribution of preferences. Second, the spatial weights matrix plays an important role in shaping the interpretation of results and should be carefully considered in spatial autocorrelation tests. In line with previous research (Johnston & Ramachandran, 2014; Raudsepp-Hearne et al., 2010), we defined 'neighboring' individuals using a queens contiguity spatial matrix. We also chose this matrix because of the nature of our data. Using a distance-defined matrix was less relevant in this study's diverse landscape where neighboring individuals were relatively close together in the northern, more urban parts of the county but much further apart in the south portion of the county. Although this analysis approach yielded useful results, other spatial weights matrices such as k-nearest neighbors and rook continuity are available (Johnston & Ramachandran, 2014). Third, we analyzed uneven spatial units which had implications for interpreting the map outputs. Some spatial patterns were more easily observed in areas that were less dense and had fewer observations. Future research in these contexts could consider using a spatially-stratified sampling approach to generate a more equal spatial representation of preferences (Louviere & Timmermans, 1990).

Our analysis approach allowed local, place-based patterns of preferences to surface, which has important implications for management and policy. The results showed clustering, regional trends, and outliers of preferences for specific landscape attributes. Such information is helpful for targeting policy efforts and assessing the feasibility of policy proposals and local projects (Campbell et al., 2008; Johnston et al., 2016; Sagebiel et al., 2017). Specifically, our findings can assist in identifying where to focus opportunities for building future recreational facilities, expanding existing open spaces and trail systems, and conserving natural landscapes such as wetlands and prairies. Also, the outputs of the study have potential to illuminate where resistance to these and other opportunities might be greatest. Spatial differences in residents' sensitivity to increases in *Unemployment Rate* may have illustrated locations that are most vulnerable to economic downturns while patterns in *Agricultural* preferences identified areas in which agrarian lifestyles were essential to local residents and therefore important to maintain.

We conclude that the application of spatial autocorrelation methods in a discrete choice experiment is a useful and underutilized tool for understanding the spatial heterogeneity of preferences. Using a random parameters logit model, we mapped preferences based on place of residence within a mixed-use landscape in Illinois and found that individual preferences varied across Will County. These results showed strong evidence for clusters of high (and low) preferences for the study's attributes. Therefore, we demonstrated the importance of allowing preferences to vary across space so that local variability in preferences not easily explained by global statistics can be detected. Because we analyzed preferences in relation to a variety of land use types, this research aids planners and land use managers in making informed decisions about the allocation of resources and the tradeoffs between public goods and services. Further, the rural-urban interface was a particularly appropriate context to answer our research question given that these areas continue to face social, environmental, and economic change. Few discrete choice experiments have accounted for spatial preference heterogeneity at the individual-level despite the benefits that emerge from understanding localized and sometimes idiosyncratic landscape preferences (Glenk et al., 2020). Though spatial processes are complex, continuing to incorporate these processes into economic valuations has important implications for broadening our understanding of preference heterogeneity across space.

CRediT authorship contribution statement

Lorraine Foelske: Conceptualization, Formal analysis, Writing - original draft. **Carena J. van Riper:** Methodology, Writing - review & editing.

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Appendix A. Main effects of six attributes and interactions effects between Bison Presence and Protected Grasslands using the RPL model (N = 386)

Attributes	Coefficients (Std. Error)			Std. Deviation (Std. Error)		
Residential Growth	−0.0313	**	(0.0134)	0.1798	***	(0.0170)
Protected Grasslands	0.1455	**	(0.0405)	0.0579	**	(0.0265)
Distance to Recreation Areas	−0.0720	***	(0.0546)	0.0606	***	(0.0066)
Agriculture	0.0225	***	(0.0025)	0.0295	***	(0.0028)
Bison Presence	0.0701	***	(0.0208)	0.0284	*	(0.0146)
Unemployment Rates	−0.3756	***	(0.0230)	0.2512	***	(0.0245)
Constant	−3.5062	***	(0.2585)	2.9067	***	(0.1989)
Bison Presence * Protected Grasslands	0.0219	***	(0.0075)		–	

Log-likelihood = −2605; Akaike information criterion (AIC) = 5240; No. of observations = 3421; Pseudo R^2 = 0.307.
*** = $p < 0.01$,** = $p < 0.05$,* = $p < 0.10$.

Appendix B. Estimated random parameters logit (RPL) model to show main effects of six attributes and interactions effects with sociodemographic variables: a) gender (binary variable where 1 is male and 0 is female) and b) age (N = 386)

Attributes	Coefficients (Std. Error)			Std. Deviation (Std. Error)		
Residential Growth	−0.0481	*	(0.0275)	0.1826	***	(0.0169)
Protected Grasslands	0.0749	**	(0.0305)	0.0575	**	(0.0271)
Distance to Recreation Areas	−0.0805	***	(0.0103)	0.0618	***	(0.0069)
Agriculture	0.0329	***	(0.0050)	0.0290	***	(0.0027)
Bison Presence	0.0355	**	(0.0148)	0.0308	**	(0.0136)
Unemployment Rates	−0.4071	***	(0.0388)	0.2531	***	(0.0235)
Constant	−3.5751	***	(0.4166)	2.9014	***	(0.2029)
Gender * Residential Growth	0.0001		(0.0006)		–	
Gender * Protected Grasslands	0.0010		(0.0007)		–	
Gender * Distance to Rec Areas	0.0001		(0.0003)		–	
Gender * Agriculture	0.0002	*	(0.0001)		–	
Gender * Bison Presence	0.0002		(0.0003)		–	
Gender * Unemployment Rates	−0.0027	***	(0.0010)		–	
Gender * Constant	−0.0175	**	(0.0073)		–	
Age * Residential Growth	0.0003		(0.0005)		–	
Age * Protected Grasslands	−0.0007		(0.0005)		–	
Age * Distance to Rec Areas	0.0002		(0.0002)		–	
Age * Agriculture	−0.0002	**	(0.0001)		–	
Age * Bison Presence	−0.0004	*	(0.0003)		–	
Age * Unemployment Rates	0.0004		(0.0006)		–	
Age * Constant	−0.0056		(0.0060)		–	

Log-likelihood = −2596; Akaike information criterion (AIC) = 5248; No. of observations = 3421; Pseudo R^2 = 0.309.
*** = $p < 0.0001$, ** = $p < 0.05$,* = $p < 0.10$.

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