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Consumers' WTP for Sustainability Turfgrass Attributes with Consideration of Aesthetic Attributes and Water Conservation Policies

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Abstract: This study estimates consumers' willingness to pay (WTP) for sustainability turfgrass attributes such as low-input and stress-tolerance attributes, while considering potential trade-off relationships between aesthetic attributes and sustainability attributes. To address our objectives, our study conducts a choice experiment and estimates two mixed logit models. The first model includes low-input, winter kill, and shade-tolerance attributes as predictor variables, and the second model extends the first model by adding interaction terms between the aesthetic and sustainability attributes. Another choice experiment is conducted under water policies with various water rate increase and watering restriction scenarios. Results from the mixed logit models show that, overall, higher low-input cost reduction, less winter-damaged, and more shade-tolerant grasses are preferred, and that the direct effect of aesthetic attributes on consumers' preferences is strong, but the indirect effects represented by the interaction terms are generally statistically insignificant. Our results indicate that consumers like to have a pretty lawn, but no strong consideration is given to the aesthetics of their lawn when selecting low-input and stress-tolerant turfgrasses. Our choice experiment under water policy scenarios suggests that water pricing is more effective than watering restriction in increasing consumer demand for water-conserving turfgrasses.

Keywords: turfgrass attribute; missing attribute; trade-off relationship; water conservation policy

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1. Introduction

Non-market valuation is an important research topic of various fields of economics and marketing research, and choice experiments (CE) are a commonly used method to conduct such research. In CE, participants are asked to choose one alternative from a set of choice tasks consisting of different bundles of attribute levels. Then, the CE data are used to estimate respondents' preferences for each attribute (or each level of an attribute). One concern about CE is that including or excluding certain characteristics of a product may lead to a biased estimator in econometrics [1–3]. Despite this concern, only limited CE studies in agricultural and environmental economics have paid attention to this issue, and CEs for turfgrass research rarely address this issue. In general, many turfgrass studies using CE have focused on estimating consumer preferences for low-input attributes such as water, mowing, and fertilizer requirements without considering a potential relationship between aesthetic attributes and attributes of low-input [4–9]. It has been well documented that enhancing low-input attributes tends to have a negative influence on the aesthetics of lawns. For example, Ghimire et al. (2016) [6] and Ghimire et al. (2019) [7] estimate the WTP for the turfgrass attribute of maintenance cost reduction but do not include turfgrass aesthetic attributes in their CE. A few exceptions include Hugie et al. (2012) [10], Yue et al. (2012) [11], and Yue et al. (2017) [12], which evaluate the value of low-input attributes of cool-season grasses along with their aesthetic attributes (color and texture). However, no potential trade-off relationships between aesthetic and low-input attributes have been investigated in the valuation of consumer preferences for the low-input attributes in these studies.

This study estimates consumers' WTP for low-input and stress-tolerance attributes of warm-season turfgrasses, while considering the potential negative effect of enhancing these attributes on the aesthetics of grasses. Our study focuses on evaluating consumer preferences for sustainability (low-input, stress-tolerance) attributes because earlier studies (e.g., [5–12]) consistently found that turfgrass consumers highly value these attributes and also suggest that it is important to develop turfgrass varieties that require fewer resources, while maintaining visual appeal and functionality (e.g., [13,14]).

Our study extends earlier studies in three ways. First, we consider the potential negative impact of enhancing low-input and stress-tolerance attributes on the aesthetic characteristics of turfgrasses in our CE. Using the CE data, mixed logit models are estimated with sustainability and aesthetic attributes as explanatory variables with and without interaction terms between each of the sustainability attributes and the color, density, and texture of grasses. Then, we test coefficients of the interaction terms for the potential trade-off relationships between variables that interact with each other. This attempt should be effective in accurately evaluating consumer preferences for the improved turfgrass attributes. In particular, from the perspective of breeders who develop new turfgrasses with enhanced traits, it would be most helpful to know how households evaluate the potential trade-off relationship between aesthetic and sustainability attributes for the development of new turfgrass varieties in the future. Second, our study evaluates consumers' preferences for the sustainability attributes of warm-season grasses by surveying households residing in the southern region. As we focus on enhancing warm-season grasses, our study incorporates the winter kill attribute with consideration of all three aesthetic attributes: color, density, and texture. Warm-season grasses, e.g., bermudagrass, tend to be sensitive to winter damage. As a result, density should be one of the important features of the aesthetics of warm-season grasses along with color and texture. Finally, our study investigates whether water conservation policies impact consumers' valuation of low-input attributes, particularly water conservation attributes. To date, many studies evaluating the effects of water conservation policies have focused on the effects of policy on water preservation [15–20]. Unlike these studies, our study evaluates the impact of these polices on the consumer preferences for the water conservation turfgrass attribute.

2. Literature Review

Most commonly used methods for the nonmarket valuation of consumer preference include conditional valuation methods (CVMs) and CEs. Comparing CEs and CVMs, CEs have been known to be a more suitable approach to estimate the marginal utility of a change in product attributes than CVMs [21], and as a result, CEs are widely used in various fields such as environmental economics [22,23] and food and agricultural economics [24–27].

Developing sustainable turfgrass varieties has been a major research interest for many university and industry breeders [28,29]. Sustainable turfgrasses have been developed to maintain the appearance and functional aspects of grasses, while minimizing the management cost and enhancing environmental preservation [13,14]. Low-input grasses have been demanded by homeowners because of prolonged droughts in many parts of the world and potential negative environmental externalities caused by the overuse of chemical inputs such as fertilizer, pesticides, and herbicides and weather variability [11]. Stress-tolerant turfgrasses have also been developed because more arable lands have become salinized, and harsher winter conditions such as bitter cold and icy weather conditions cause more damage or death of grasses.

Ghimire et al. (2016) [6] attempt to elicit homeowners' preferences for low-input attributes such as water requirements and maintenance costs for lawn care and stress-tolerance attributes such as lost lawn area to winter kill, shade-tolerance, and salinity tolerance. Empirical results indicate that participants most prefer a low-maintenance cost, and the second, third, and fourth preferred attributes are a lower water requirement, shade-tolerance, and saline tolerance, respectively. Ghimire et al. (2019) [7] extend the previous study by considering group heterogeneity. Two groups such as "Willing hobby gardeners" and "Reluctant mature homeowners" are identified, and the results show that, in both classes, the WTP for low and medium water requirements are the first and second highest. The two earlier studies find that the warm-season turfgrass varieties with low-input attributes are attractive choices to southern households. Knuth et al. (2023) [9] also estimate preferences for low-input attributes such as the level of irrigation and fertilizer use using a latent class model and find that "Irrigation conscious" and "Fertilizer conscious" groups have more knowledge of lawn care compared to other groups. Ge et al. (2020) [5] extend earlier studies by controlling respondents' attribute non-attendance (ANA) while estimating producers' preferences for low-input attributes. The study finds drought tolerance to be the most preferred attribute for sod producers with and without controlling ANA. Hildebrand et al. (2022) [8] also examine the effect of ANA in estimating consumer preferences for low-input turfgrass attributes and find that estimates of the willingness to accept by producers for all low-input attributes are statistically significant after controlling ANA. Yet, the appearance of turfgrass could also be an important factor when households choose turfgrass varieties [11]. Hugie et al. (2012) [10], Yue et al. (2012) [11], and Yue et al. (2017) [12] include aesthetic attributes, along with low-input attributes, in their CEs. Hugie et al. (2012) [10] finds that low-input attributes are preferred to aesthetic attributes. Yue et al. (2012) [11] also consider a set of aesthetic attributes, low-input attributes, and other turfgrass characteristics for their model specifications and conclude that low-input attributes are as important as aesthetic attributes. Yue et al. (2017) [12] assess the WTP for low-input attributes and aesthetic attributes for residents of the U.S. and Canada, and find that low-input attributes are more valuable traits than aesthetic traits, which is consistent with the findings from Hugie et al. (2012) [10].

Although three studies [10–12] consider aesthetic attributes in CEs, the studies do not directly test for the potential interaction, trade-offs, effects between low-input and aesthetic attributes. The earlier studies also focus only on the color and texture of cool-season grass, while our study examines the interaction effects for warm-season grass, considering the color, density, and texture of the grasses. In this context, Meas et al. (2015) [27] suggest that marginal effects of interacting terms between pairs of attributes be considered along with direct effects for better estimates of the marginal effects of attributes. For example, a few studies in environmental economics (e.g., [22,30]) and food economics (e.g., [31,32]) use coefficients of interaction terms between attributes to identify trade-off relationships. In a typical lawn-management practice, the input use (e.g., the amount of water sprayed) and appearance of the lawn (e.g., color of lawn) could closely interact with each other.

Various water conservation policies (e.g., increasing water rates and limiting lawn watering) have been implemented in drought areas, particularly in southern and midwestern parts of the U.S., and many earlier studies evaluate the effects of these policies (e.g., [15–20]). For non-price policies, studies find that mandatory water restriction policies are more effective than voluntary water conservation policies [15,18]. Kenney et al. (2004) [15] show that once-a-week watering restrictions decrease water consumption more than twice-a-week restrictions. On the other hand, Ozan and Alsharif (2013) [17] find that water consumption decreases with the number of watering restrictions, i.e., twice-a-week watering restriction is more effective than once-a-week restriction. Overall, the studies conclude that policies restricting outdoor water use or increasing water rates are effective in saving domestic water. The studies also note that the demand for low-input turfgrass could increase under regulations associated with water conservation. Restrictions on water use could make homeowners face challenges in maintaining a healthy and good-looking lawn. As a result, this could affect consumers' valuations of low-input attributes, particularly water-conserving attributes. To date, no studies directly estimate how water conservation regulations affect the demand for low-input turfgrass. In this paper, we examine how water conservation policies such as outdoor watering restrictions and water rate increases affect consumer preferences for low-input turfgrass attributes when the trade-off relationship between low-input and aesthetic attributes is considered.

3. Materials and Methods

3.1. Model

A random utility model that describes how an individual's (i) utility is formed by selecting an alternative, j, in a choice set, t, can be written as [33]:

$$U_{ijt} = X_{ijt}\beta + \varepsilon_{ijt}, \tag{1}$$

where the utility function, U_{ijt}, consists of a deterministic component, $X_{ijt}\beta$, and a stochastic part, ε_{ijt}. X_{ijt} can be defined as observed product attributes and β as corresponding coefficients. ε_{ijt} is an independently and identically distributed (i.i.d.) random error term. Allowing individuals' preference heterogeneity, we can specify a mixed logit model (MXL) as:

$$U_{ijt} = X_{ijt}\beta_i + \varepsilon_{ijt}, \tag{2}$$

where β_i, an individual-specific parameter, follows a multivariate distribution, $\beta_i \sim f(\mathrm{b}, \Sigma)$, with a mean, b, and variance–covariance matrix, Σ.The error term, ε_{ijt}, is assumed to have the extreme value distribution. After estimating Equation (2), one can calculate a consumer i's WTP for attribute x as [34]:

$$WTP_{x_i} = \frac{\frac{\partial U}{\partial x}}{\frac{\partial U}{\partial PP}} = \frac{\beta_{x_i}}{\beta_{pp}},$$

where PP represents a purchase price of sod per square foot. β_{x_i} and β_{pp} denote estimated parameters for x and PP, respectively.

To derive an empirical model of (2), we use effect coding rather than dummy coding for all categorical variable levels to recover marginal preferences and the WTP for base levels [35]. Using the recovered baseline preference estimates, it is possible for us to calculate the relative importance of attributes, i.e., WTP rankings over attributes are calculated after estimating the WTP by attribute level. Estimates of WTP rankings by attribute, rather than attribute level, are expected to provide useful information for the research priority of attributes for breeders and policy makers.

An empirical model considering low-input and, stress-tolerance attributes, as well as aesthetic attributes (a model without interaction terms), is specified as: (Subscripts, i, j, and t, are henceforth suppressed for the sake of notational simplicity).

$$\begin{aligned} U = \beta_1 ASC + \beta_2 WR1 + \beta_3 WR2 + \beta_4 MR1 + \beta_5 MR2 + \beta_6 FR1 + \beta_7 FR2 + \beta_8 WK1 \\ + \beta_9 WK2 + \beta_{10} ST + \beta_{11} CO + \beta_{12} DE + \beta_{13} TE + \beta_{14} PP + \varepsilon, \end{aligned} \tag{3}$$

where ASC is the alternative specific constant to measure the utility of the status quo: ASC = 1 if no purchase of new turfgrass is selected, i.e., the status quo, and ASC = -1 otherwise. $WR1$ and $WR2$ represent the percentage reduction in water cost: $WR1$ = 1 if the level of the water cost reduction is 40% (medium), $WR1$ = 0 otherwise; $WR2$ = 1 if the level of water cost reduction is 50% (high), $WR2$ = 0 otherwise; and a 30% water cost reduction (low) is the base level. $MR1$ and $MR2$ represent mowing cost reduction: $MR1$ = 1 if the level of mowing cost reduction is 10% (medium), $MR1$ = 0 otherwise; $MR2$ = 1 if the level of mowing cost reduction is 15% (high), $MR2$ = 0 otherwise; and a 5% mowing cost reduction (low) is the base level. $FR1$ and $FR2$ refer to fertilizer, pesticide, and herbicide cost reduction: $FR1$ = 1 if the level of cost reduction for fertilizer, pesticide, and herbicide is 10% (medium), $FR2$ = 0 otherwise; $FR2$ = 1 if the level of fertilizer, pesticide, and herbicide cost reduction is 15% (high), $FR2$ = 0 otherwise; and a 5% reduction in fertilizer, pesticide, and herbicide cost is the base level. $WK1$ and $WK2$ represent lost lawn area to winter kill: $WK1$ = 1 if the level of lost lawn area due to winter kill is 20% (medium), $WK1$ = 0 otherwise; $WK2$ = 1 if the lost lawn area to winter kill is 0% (low), $WK2$ = 0 otherwise; and 40% damage (high) is the base level. ST = 1 if the turfgrass possesses shade-tolerance characteristics, ST = −1 otherwise; and ST = −1 is the base level. CO (color), DE (density), and TE (texture) in Equation (3) are aesthetic attribute variables. Following the effect coding approach, CO, DE, and TE are coded as 1 if the turfgrass is light green, low density, and fine texture, respectively. A dark green color, high density, and coarse texture are coded as −1. Price variable (PP) represents the sod purchase price per square foot. The levels of attributes specified in Equation (3) were chosen from references in the turfgrass literature [5–8,10–12,36] after consultation with experts in turfgrass breeding and extension.

Equation (3) can be extended by incorporating interaction terms between aesthetic attributes and low-input/stress-tolerance attributes as:

$$U = \beta_1 ASC + \sum_{a=1}^{3} \beta_{1a} AE_a + \sum_{b=1}^{6} \beta_{2b} CR_b + \sum_{c=1}^{3} \beta_{3c} ET_c + \sum_{a=1}^{3}\sum_{b=1}^{6} \beta_{4ab} AE_a * CR_b + \sum_{a=1}^{3}\sum_{c=1}^{3} \beta_{5ac} AE_a * ET_c + \beta_6 PP + \varepsilon, \quad (4)$$

where AE_a denotes aesthetic attributes such as color (CO), density (DE), and texture (TE). CR_b represents low-input attributes such as water ($WR1$ and $WR2$), mowing ($MR1$ and $MR2$), and fertilizer, pesticide, and herbicide cost reduction ($FR1$ and $FR2$). ET_c includes the lost lawn area to winter kill ($WK1$ and $WK2$) ratio and shade-tolerant sod (ST). $AE_a * CR_b$ are interaction terms between aesthetic and low-input attributes. $AE_a * ET_c$ are interaction terms between aesthetic and stress-tolerance attributes.

We estimate our MXLs in the form of WTP space to directly estimate the WTP of each attribute level. Therefore, rewriting Equation (3) in the WTP space yields [37]:

$$\begin{aligned} U = \beta_{14} * (&\beta_1/\beta_{14} ASC + \beta_2/\beta_{14} WR1 + \beta_3/\beta_{14} WR2 + \beta_4/\beta_{14} MR1 + \beta_5/\beta_{14} MR2 + \beta_6/\beta_{14} FR1 + \beta_7/\beta_{14} FR2 \\ &+ \beta_8/\beta_{14} WK1 + \beta_9/\beta_{14} WK2 + \beta_{10}/\beta_{14} ST + \beta_{11}/\beta_{14} CO + \beta_{12}/\beta_{14} DE + \beta_{13}/\beta_{14} TE + PP) + \varepsilon, \end{aligned} \quad (5)$$

where from β_1/β_{14} to β_{13}/β_{14} are coefficients of independent variables, representing the WTP for each level of attribute.

Equation (4) can be rewritten in the WTP space similarly.

Interpretation of WTP estimated from the effect coding approach needs to be different from WTP estimated from the dummy coding approach [38]. Hu et al. (2022) [38] describe the role of the omitted base level for each attribute. Different from the dummy coding scheme, the base level WTP values can be calculated by multiplying −1 to the sum of all estimated WTP values for each level of attribute [38]. Then, the interpretation of the WTP for level t, WTP_{β_t}, is calculated as:

$$WTP_{\beta_t} = \left(WTP_{\hat{\beta}_t} - WTP_{\hat{\beta}_{base\ level}} \right), \quad (6)$$

where $WTP_{\hat{\beta}_t}$ is the estimated WTP for attribute level t, and $WTP_{\hat{\beta}_{base\ level}}$ is the recovered based level WTP [38]. We report WTP_{β_t} rather than $WTP_{\hat{\beta}_t}$ for the convenience of interpreting the WTP values. Therefore, WTP_{β_t} indicates the WTP for each attribute level relative to the base level, which is the difference between the WTP for each attribute level and the base level WTP. Hu et al. (2022) [38] state that the estimated WTP values from dummy and effect codes look different because each coding method codes the base level differently. However, a proper conversion process such as Equation (6) can result in the same interpretation for WTP values from the two coding methods (in many studies using effect coding, the WTP from effect coding multiplied by 2 is typically considered the same as the WTP from the dummy coding due to the difference in base coding. However, Hu et al. (2022) [38] demonstrate that this interpretation is appropriate only when the attribute level is two. When the level of attribute is more than two, a more general method such as Equation (6) needs to be used for the interpretation of estimated WTP values from effect coding. A numeric example of comparing estimates from effect coding vs. dummy coding has been provided in Appendix A).

In addition to estimating consumer WTP by attribute level, we also estimate rankings of consumer WTP for each attribute. As discussed earlier, WTP by attribute level can only be interpreted relative to the base value due to the non-linearity of the coding scheme.

Therefore, in order to examine consumer WTP ordering by attribute, not by attribute level, we need to establish rankings of consumer WTP by attribute. The WTP rankings by attribute could help identify research and marketing priorities among attributes that could be potentially enhanced. Based on the estimated WTP values, the relative importance of each attribute can be calculated as the proportion of the range of WTP values for an attribute to the sum of WTP ranges from all attributes, and can be written in percentage form as [6]:

$$Relative\ Importance_a = \left(\frac{Range\ of\ WTP_a}{\sum_{a=1}^{n} Range\ of\ WTP_a} \right) \times 100, \tag{7}$$

where $Range\ of\ WTP_a$ is the range of WTP values (by attribute level) for an attribute, which is calculated by subtracting the lowest WTP from the highest WTP; n is the total number of attributes considered in our study. Then, the WTP rankings can be determined based on the relative importance obtained from Equation (7).

3.2. Survey Design and Data

A web-based choice experiment was conducted between 19 April and 10 May 2021. Our target population is homeowners aged over 18 years residing in 11 southern states because our study focuses on estimating homeowners' preferences for warm-season grasses. The 11 states include Texas, Oklahoma, Arkansas, Louisiana, Tennessee, Mississippi, Alabama, Florida, Georgia, South Carolina, and North Carolina. Our survey panel was selected from the Qualtrics Panels to meet the target demographic by gender, race, and sample size for each state. A pilot survey was conducted on April 19 with 50 individuals to find potential problems of the survey and refine survey questions before starting an actual survey (the survey (IRB-21-93) was approved by the Institutional Review Board (IRB) at Oklahoma State University).

The survey included 2 screening questions to filter out participants who are not over 18 or rent a house, 24 (12 questions without policy scenarios and another 12 questions with policy scenarios) choice tasks to obtain households' choice of turfgrass with a bundle of attributes, and several questions regarding individuals' socio-demographic characteristics.

To determine turfgrass attributes and levels of attributes for our experiment, previous turfgrass studies were first reviewed, and among the turfgrass attributes considered in previous studies, a series of low-input attributes, stress-tolerance attributes, and aesthetic attributes were selected. Then, we consulted with experts in turfgrass breeding and extension before finalizing the attributes and levels of each attribute to be used for our survey. Especially, aesthetic attributes such as color, density, and texture, as well as the levels of each attribute were selected based on the National Turfgrass Evaluation Program (NTEP) guidelines [36] and previous turfgrass studies [5–8,10–12]. Two levels of aesthetic attributes were used for the sake of brevity in model specification and the interpretation of econometric results. Additionally, to help respondents understand aesthetic attributes, pictures of grasses taken from experiment plots were embedded in each conjoint choice set. We included low-input attributes (water cost reduction, mowing cost reduction, and fertilizer, pesticide, and herbicide cost reduction) and stress-tolerance attributes (reduced winter kill and shade-tolerant sod). The price of sod per square foot was also included for a payment vehicle. The summary of turfgrass attributes and attribute levels used in the choice experiment is reported in Table 1.

Table 1. Turfgrass Attributes and Attribute Levels.

Attributes	Attribute Levels	Variables
Water cost reduction	Low (30% less/month)	Base level
	Medium (40% less/month)	WR1
	High (50% less/month)	WR2
Mowing cost reduction	Low (5% less)	Base level
	Medium (10% less)	MR1
	High (15% less)	MR2
Fertilizer, pesticide, and herbicide cost reduction	Low (5% less)	Base level
	Medium (10% less)	FR1
	High (15% less)	FR2
Lost lawn area to winter kill	Low (0%)	WK2
	Medium (20%)	WK1
	High (40%)	Base level
Shade tolerance	No	Base level
	Yes	ST
Color	Light green	CO
	Dark green	Base level
Density	Low	DE
	High	Base level
Texture	Fine	TE
	Coarse	Base level
The purchase price of sod per square foot	\$0.20, \$0.30, \$0.40, \$0.50	PP

Given the number of attributes and levels of these attributes, the total combination of attributes for the full factorial design is 5184 ($2^4 \times 3^4 \times 4$). However, to find a more manageable set of choices, we used a fractional factorial design that yields 72 choice sets with a D-efficiency of approximately 100%. Then, based on the generated 72 choice sets, 6 blocks with 12 choice sets were created, and each choice set had three options: options A, B, and C, where option A and B represented a combination of turfgrass attributes and levels, and option C was for an opt-out or no-purchase selection, the status quo. As a result, our experiment provided each participant with 12 randomly ordered choice tasks from a randomly selected block out of the 6 blocks. Figure 1 shows an example of a choice task with a turfgrass profile provided to respondents. Figure 1 is an example of 12 choice tasks from 6 blocks that were randomly provided to survey participants. As indicated earlier, the levels of each attribute presented in Figure 1 were determined after reviewing prior studies and consultation with turfgrass researchers and extension professionals. From the survey experiment, we initially obtained 14,388 (12 choice sets $\times$ 1199 individuals) observations (i.e., choice responses). To improve the quality of the CE data, we excluded participants who selected the same option throughout all 12 choice experiments and those who completed 12 choice questions in less than 60 s, which resulted in 10,980 (915 individuals) observations for our econometric analysis [39] (Fessler et al. (2022) [39] removed respondents who spent less than 4 min to complete the whole survey (including four choice tasks and demographic questions) and who showed questionable responses during choice experiments. Previous studies also used trap questions [40], eye-tracking [5], and attribute non-attendance (ANA) analysis [41] to address participant inattention problems).

Option A and B represent two different sets of sod/turfgrass characteristics. Which option (A, B, or C) would you be most likely to purchase?			
Attributes	Option A	Option B	Option C
Picture			If A or B were the only available options, I would not purchase new sod for my lawn.
Color	Dark green	Light green	
Texture	Coarse	Fine	
Density	High	Low	
Water cost reduction	Low (30% less/month)	High (50% less/month)	
Mowing cost reduction	Medium (10% less)	Low (5% less)	
Fertilizer, pesticide, and herbicide cost reduction	Medium (10% less)	Low (5% less)	
Lost lawn area to winter kill	High (40%)	Medium (20%)	
Shade tolerant sod	Yes	No	
The average purchase price of sod per square foot	$0.30	$0.50	

Figure 1. An Example of Choice Set.

Moreover, to examine the impact of water conservation policies on consumer preferences for water cost reduction attributes, two types of water policies were considered in this study: water rate increase (price policy) and restriction of the number of outdoor water use (non-price policy). For the price policy, we used three hypothetical scenarios such as 25%, 50%, and 100% increases in the water rate. For the non-price policy, three different levels of outdoor water-use restriction were selected: (1) odd or even days, (2) two days a week, and (3) one day a week (irrigation restriction policies typically include a combination of total irrigation hours a week, time of irrigation, and voluntary or mandatory participation. Since it is difficult to consider all these combinations in our experimental design, this study focuses on the frequency of outdoor watering). Our study used a within-subject design to minimize the random noise that could be caused by differences in subjects' characteristics such as personal history, background knowledge, and anything not controlled through model specification [42].

Descriptive statistics of individual demographic characteristics from our sample are presented in Table 2. The mean age of our sample is around 51, and the gender proportion is 49% of male and 51% of female, respectively. Respondents with at least a high school diploma are approximately 27%, while over 73% of the respondents have at least a bachelor's degree. About 33% of survey participants earn less than USD 50,000 in annual income, while about 32% of participants earn more than USD 100,000 each year.

Table 2. Descriptive Statistics of Individuals' Demographic Characteristics.

Variables	Mean/Proportion
Age	50.56 (17.90)
Gender	
Male	0.49
Female	0.51
Education	
Less than high school	0.01
High school graduate	0.26
Undergraduate degree	0.43
Graduate degree	0.31
Income	
<$25,000	0.12
$25,000–$49,999	0.21
$50,000–$74,999	0.21
$75,000–$99,999	0.14
$100,000–$124,999	0.08
$125,000–$149,999	0.09
$150,000–$174,999	0.06
$175,000–$199,999	0.04
>$200,000	0.06

The number in parenthesis is standard deviation.

4. Results and Discussion

Our study estimates two empirical models with and without interaction terms using Equations (3) and (4). The first model (without interaction terms) includes three cost reduction attributes (low-input attributes), lost lawn area to winter kill and shade-tolerance attributes, and three aesthetic attributes as predictor variables. The second model adds interaction terms between aesthetic attributes and low-input, winter kill, and shade-tolerance attributes to examine whether trade-off relationships exist between aesthetic attributes and other attributes considered in this study. A total of 27 interaction terms are created between nine levels of low-input and stress-resistance attributes and three aesthetic attributes (color, density, and texture). To avoid a high correlation between interaction terms and help model convergence, we estimated three different models, where each specification included nine interaction terms (between each of the three aesthetic attributes and nine levels of low-input and stress-resistance attributes).

Our empirical models are estimated using Stata with the *mixlogitwtp* command and R with *Apollo* (version 0.3.0) [43]. The estimation of mixed logit models requires a multinomial integral for a mixing distribution, which requires a numerical evaluation because it is typical that the integral does not have the closed form. We tried both the Halton draw method [44] and the pseudo-Monte Carlo draw method [43], and found that both methods yielded almost the same results. Our study presents results from the Halton draw method. The price coefficient is assumed to follow log-normal distribution to ensure the negative coefficient. The remaining coefficients are allowed to be random under the normal distribution. Estimates are WTP values because the WTP space approach is used in our study.

Estimates of WTP values are reported in Table 3. The negative estimates of the ASC from both models indicate that the overall consumer demand for sustainability attributes increased because we set $ASC = 1$ for the status quo, $ASC = -1$ otherwise. For the water cost reduction attribute, all four columns show that the WTP values for 40% and 50% water cost reduction are higher than the base-level 30% water cost reduction. For example, the WTP values of 40% and 50% water cost reduction from the model without interaction terms are $0.0713 and $0.1228 higher than the base-level per square foot of the sod. The WTP estimates of water cost reduction from the model with interaction terms are $0.0517, $0.0790, and $0.0765 (40% cost reduction) and $0.1139, $0.1225, and $0.1322 (50% water cost reduction) higher than the base-level from the color, density, and texture equations, respectively. All the estimates are statistically significant at the 1% level. The results indicate that consumers prefer turfgrasses with a higher water cost reduction than with a lower water cost reduction. The estimates of a 10% reduction in mowing and 10% reduction in chemical spray (fertilizer, pesticide, and herbicide) costs are not statistically significant from both models. However, the 15% reductions in mowing and chemical spray costs are mostly statistically significant with positive estimates at least at the 10% level, indicating consumers' higher preference for the 15% management cost reduction in mowing and chemical spray than the base-level of 5% cost reduction.

Table 3. Estimates of Mixed Logit Model with and without Interaction Terms.

	Without Interaction Terms	**With Interaction Terms**		
Attributes		**Color (Light Green)**	**Density (Low)**	**Texture (Fine)**
Direct effect				
ASC	−1.2968 *** (0.1457)	−1.2721 *** (0.1726)	−1.3211 *** (0.1045)	−1.3044 *** (0.1140)
WR1	0.0713 *** (0.0168)	0.0517 *** (0.0241)	0.0790 *** (0.0229)	0.0765 *** (0.0219)
WR2	0.1228 *** (0.0223)	0.1139 *** (0.0314)	0.1225 *** (0.0314)	0.1322 *** (0.0270)
MR1	0.0009 (0.0154)	0.0131 (0.0190)	0.0037 (0.0316)	−0.0015 (0.0168)
MR2	0.0261 * (0.0144)	0.0366 * (0.0165)	0.0202 * (0.0159)	0.0183 (0.0154)
FR1	0.0016 (0.0181)	0.0027 (0.0162)	−0.0030 (0.0221)	0.0117 (0.0239)
FR2	0.0226 (0.0189)	0.0264 ** (0.0191)	0.0430 ** (0.0242)	0.0363 ** (0.0199)
WK1	0.1290 *** (0.0212)	0.1211 *** (0.0247)	0.1251 *** (0.0425)	0.1174 *** (0.0241)
WK2	0.1843 *** (0.0299)	0.1741 *** (0.0323)	0.1701 *** (0.0447)	0.1696 *** (0.0330)
ST	0.1129 *** (0.0175)	0.1277 *** (0.0216)	0.1366 *** (0.0167)	0.1264 *** (0.0213)
CO	−0.1829 *** (0.0293)	−0.1785 *** (0.0252)	−0.1506 *** (0.0192)	−0.1869 *** (0.0403)
DE	−0.1660 *** (0.0326)	−0.1607 *** (0.0216)	−0.1563 *** (0.0242)	−0.1716 *** (0.0238)
TE	−0.0080 (0.0167)	−0.0053 (0.0190)	−0.0065 (0.0337)	0.0067 (0.0187)
Indirect effect (from interaction terms with aesthetic attributes)				
WR1	-	0.0014 (0.0301)	0.0228 (0.0261)	−0.0150 (0.0301)
WR2	-	−0.0214 (0.0314)	0.0414 (0.0305)	0.0190 (0.0281)
MR1	-	0.0016 (0.0325)	−0.0069 (0.0644)	−0.0244 (0.0258)
MR2	-	0.0441 (0.0355)	0.0217 (0.0285)	0.0165 (0.0266)
FR1	-	−0.0261 (0.0320)	−0.0086 (0.0364)	−0.0024 (0.0299)
FR2	-	−0.0209 (0.0347)	−0.0010 (0.0212)	0.0050 (0.0250)
WK1	-	0.0043 (0.0283)	−0.0236 (0.0277)	−0.0005 (0.0281)
WK2	-	−0.0238 (0.0280)	−0.0261 (0.0335)	−0.0181 (0.0281)
ST	-	−0.0457 (0.0436)	−0.0890 *** (0.0275)	0.0201 (0.0297)
Number of observations	10,980	10,980	10,980	10,980

Standard errors are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. WR1 and WR2 denote 40% and 50% water cost reduction; MR1 and MR2 represent 10% and 15% mowing cost reduction; FR1 and FR2 indicate 10% and 15% fertilizer, pesticide, and herbicide cost reduction; WK2 and WK1 represent 20% and 0% lost lawn area to winter kill; and ST refers to shade-tolerance.

The estimates of winter kill and shade-tolerance are all positive and statistically significant at the 1% level. Our results indicate that consumers very strongly prefer less winter-damaged grass (20% and 0% lawn lost) to more winter-damaged grass (40% lawn lost) and also present strong preference for shade-tolerant grass. Finally, the estimates of aesthetic attributes show that color and density are important aesthetic attributes (statistically significant at the 1% level). Homeowners prefer dark-green and high-density grass to light-green and low-density grass. Both winter kill and density have not been considered in earlier studies that evaluate consumer preference for low-input attributes. The second half of Table 3, reporting indirect effects of the aesthetic attributes, shows that only one interaction term between density and shade-tolerance is statistically significant at the 1% level. The negative estimate, −0.0890, indicates an inverse correlation or trade-off relationship between the two attributes, i.e., consumers lower their WTP values by $0.0890 per square foot of sod due to the deteriorated density of shade-tolerant grass. Results from the interaction terms, except the interaction term between shade-tolerance and density, show that the trade-offs between low-input/stress-tolerant and aesthetic attributes in consumers' valuations are weak, although the direct effects of aesthetic attributes are still strong, particularly for color and density. Our findings indicate that our consumers like to have their lawns look pretty, but no strong consideration is given to the aesthetics when selecting enhanced low-input and stress-tolerant turfgrasses.

We combine the direct and indirect effects to calculate WTP values for each sustainability (low-input and stress-tolerant) attribute, and the results are reported in Table 4. The results show that most WTP estimates are statistically significant at least at the 10% level except for estimates of mowing cost reduction and chemical spray cost reduction. Overall, higher low-input cost reduction, less winter kill, and more shade-tolerant grasses are preferred even though the interaction terms are generally statistically insignificant in some cases.

Table 4. WTP Values with Interaction Terms.

Attributes	Color (Light Green)	Density (Low)	Texture (Fine)
WR1	0.0531 (0.0401)	0.1018 *** (0.0353)	0.0614 * (0.0364)
WR2	0.0924 ** (0.0444)	0.1639 *** (0.0408)	0.1512 *** (0.0394)
MR1	0.0146 (0.0390)	−0.0032 (0.0637)	−0.0259 (0.0309)
MR2	0.0807 ** (0.0397)	0.0418 (0.0319)	0.0348 (0.0308)
FR1	−0.0234 (0.0364)	−0.0115 (0.0506)	0.0093 (0.0377)
FR2	0.0055 (0.0409)	0.0421 (0.0379)	0.0413 ** (0.0315)
WK1	0.1253 *** (0.0360)	0.1015 ** (0.0504)	0.1168 *** (0.0373)
WK2	0.1503 *** (0.0405)	0.1440 *** (0.0511)	0.1515 *** (0.0438)
ST	0.0819 * (0.0479)	0.0477 (0.0314)	0.1466 *** (0.0362)

Standard errors are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. WR1 and WR2 denote 40% and 50% water cost reduction; MR1 and MR2 represent 10% and 15% mowing cost reduction; FR1 and FR2 indicate 10% and 15% fertilizer, pesticide, and herbicide cost reduction; WK2 and WK1 represent 20% and 0% lost lawn area to winter kill; and ST refers to shade-tolerance.

The WTP values reported in Tables 3 and 4 are not comparable across attributes because the estimated WTP values are relative to the base level of each attribute. However, comparing consumer preference over attributes, not levels of attributes, could provide important information for researchers, particularly breeders, for their research priorities. The relative importance (RI) of each attribute is calculated using Equation (7) and reported in Table 5. The results show that homeowners' most preferred attribute is lost lawn area to winter kill except in the model with interaction terms with density. The results for water cost reduction and shade-tolerance are mixed, but these two attributes are the second- or the third-most important attributes in most cases except in the model with the interaction term density. In this model, the water cost reduction is the most important attribute. As observed in earlier tables, the mowing cost and chemical spray cost reduction attributes are not as important as water cost reduction, winter kill, and shade-tolerance attributes in Table 5.

Table 5. Rankings of Consumers' WTP over Turfgrass Attributes.

	Without Interaction Terms		With Interaction Terms					
			Color (Light Green)		Density (Low)		Texture (Fine)	
Attributes	**Relative Importance (%)**	**Ranking**	**Relative Importance (%)**	**Ranking**	**Relative Importance (%)**	**Ranking**	**Relative Importance (%)**	**Ranking**
WR	19.37 (−0.06 0.13)	3	19.75 (−0.09 0.09)	2	46.98 (−0.27 0.16)	1	33.79 (−0.21 0.15)	2
MR	5.43 (−0.03 0.03)	4	17.24 (−0.08 0.08)	4	0.00 (0.00 0.00)	4	0.00 (0.00 0.00)	4
FR	0.00 (0.00 0.00)	5	0.00 (0.00 0.00)	5	0.00 (0.00 0.00)	4	0.00 (0.00 0.00)	4
WK	51.72 (−0.31 0.18)	1	45.50 (−0.28 0.15)	1	42.58 (−0.25 0.14)	2	38.99 (−0.27 0.15)	1
ST	23.47 (−0.11 0.11)	2	17.51 (−0.08 0.08)	3	10.43 (−0.05 0.05)	3	27.22 (−0.15 0.15)	3

Minimum and maximum WTP values (the range of WTP values) are in parentheses. WR and MR denote water cost reduction and mowing cost reduction; FR represents fertilizer, pesticide, and herbicide cost reduction, and WK and ST refer to lost lawn area to winter kill and shade-tolerance, respectively.

We conducted another discrete choice experiment under various water policy scenarios: water rate increases by 25%, 50%, and 100%, and watering restrictions on even or odd days in a week, two days a week, and one day a week. For the experiment, one scenario out of the six policy scenarios was randomly provided to each respondent. The WTP values for levels of enhanced sustainability attributes were estimated with a model without interaction terms because most interaction terms were not statistically significant in the models with interaction terms (Table 3). The estimation results are compared with those without the water policy restrictions. Table 6 presents the effects of the water policies on the WTP values for the 50% water cost reduction attribute (we also estimated the same water policy effects on the attribute of 40% water cost reduction and found similar results (the policy of 25% water rate increase effectively raised the WTP at the 1% level), but overall the policy effects were lower than the results from the attribute of 50% water cost reduction). In Table 6, most WTP values before and after implementing the water policies are statistically significant at least at the 10% level and show a positive effect of water policies in increasing WTP values for the water cost reduction attribute. When policy effects are tested, policies with 25% and 50% increases in the water rate result in a statistically significant effect in increasing WTP values for the water-conserving attribute. However, the *t*-test result shows that the 100% water rate increase is not effective in changing the consumer preference for the 50% water cost reduction attribute. Our result indicates that the consumer response to increasing water rate policies is nonlinear. Consumers change their preference for the water cost reduction attribute the most at the rate of a 25% increase, then the change in the WTP diminishes as the water rate further increases. No statistical difference is found from the *t*-test comparing before and after implementing the water policy of restricting lawn watering. The results suggest that the water pricing policy is more effective than watering restrictions in increasing consumer demand for water-conserving turfgrasses.

As indicated earlier, no earlier studies evaluated the effects of water policy on consumer demand for water-conserving turfgrass attributes. However, several studies evaluated the effects of water policies on water preservation, and only a few studies found that a water rate increase was effective in reducing water consumption [16,19,20]. For example, Olmstead and Stavins (2009) [16] showed that water price increases were more effective than non-price policy (e.g., outdoor water-use restriction) in reducing water consumption. Baerenklau, Schwabe, and Dinar (2014) [19] reported that increasing the water rate decreased the water demand by around 17% in Southern California. Smith (2022) [20] also found that a few groups of households sufficiently reduced water bills in response to the water-price increase policy, although households living in Denver, Colorado did not respond to increasing the water rate in general.

Table 6. Change in WTP for 50% Water Cost Reduction under Water Policy Scenarios.

Policy Scenario	Attribute	WTP_{before}	WTP_{after}	*t*-Test to Compare WTPs
25% water rate increase	50% water cost reduction	0.0912 *** (0.0335)	0.9267 *** (0.1384)	0.8356 *** (0.1424)
50% water rate increase	50% water cost reduction	0.0720 * (0.0431)	0.3326 *** (0.1179)	0.2606 ** (0.1255)
100% water rate increase	50% water cost reduction	0.1800 *** (0.0468)	0.2128 *** (0.0488)	0.0328 (0.0676)
Restriction for the watering lawn: Even or odd days a week	50% water cost reduction	0.0811 ** (0.0323)	0.0932 *** (0.0305)	0.0121 (0.0445)
Restriction for the watering lawn: Two days a week	50% water cost reduction	0.2495 (0.7274)	0.2629 *** (0.0400)	0.0134 (0.7285)
Restriction for the watering lawn: One day a week	50% water cost reduction	0.2663 *** (0.0614)	0.4117 ** (0.1978)	0.1454 (0.2071)

Standard errors are in parentheses. ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

5. Conclusions

Developing low-input attributes could be a way to address water scarcity and environmental problems caused by severe drought and the overuse of fertilizers, herbicides, and pesticides. Our paper extends earlier studies by incorporating aesthetic attributes along with low-input and stress-tolerance attributes (sustainability attributes) in mixed logit models and examines potential trade-off relationships between aesthetic attributes and sustainability attributes.

Results from the mixed logit models show that overall, higher low-input cost reductions, less winter kill, more shade-tolerance, and prettier grasses are preferred. Estimates of interaction terms, other than the interaction term between shade-tolerance and density, show that trade-offs between low-input/stress-tolerance and aesthetic attributes in consumers' valuations of the low-input and stress-tolerance attributes are statistically insignificant. Our results indicate that consumers like to have a pretty lawn, but no strong consideration is given to the aesthetics when selecting low-input and stress-tolerant turfgrasses. Our discrete choice experiment under various water policy scenarios suggests that water pricing is more effective than watering restrictions in increasing consumer demand for water-conserving turfgrasses.

Our findings provide useful implications for future research in turfgrass breeding and the evaluation of consumer preferences for turfgrass. Many researchers have discussed potential degradation of aesthetic characteristics when developing input-saving turfgrass varieties. However, to the best of our knowledge, no earlier studies have investigated the effect of aesthetic deterioration caused by enhanced low-input and stress-tolerance attributed on consumers' valuation of turfgrasses. Our findings suggest that aesthetic attributes need to be considered when conducting choice experiments for the valuation of the enhanced grasses, but limiting trade-offs may not be as important as enhancing low-input/stress-tolerance attributes when developing future turfgrasses. Early studies [10–12] also found that aesthetic attributes are statistically significant in affecting consumer preferences but do not consider potential trade-off relationships. Another contribution might be the water policy outcomes from our choice experiment. Our experiment finds that water pricing is more effective than watering restrictions in increasing consumer demand for water-conserving grasses, which could help develop better water policies in the future.

As shown in our results, we found no strong trade-off relationship between enhanced attributes and aesthetic attributes in the valuation of consumer preferences overall. To further investigate this issue, more choice experiments need to be conducted with different demographic characteristics and geographic areas. Different econometric procedures such as hybrid-choice models [45,46] could also be estimated with the consideration of other factors (than those already included in our survey) that could affect homeowners' preferences of grasses. Examples of these factors could be individuals' own risk perceptions, homeowners' perceptions of what neighbors think about their lawn, and the neighborhood environment. Another caveat of our study, particularly in interpreting our water policy effect, is that our study only considers two relatively simple water conservation policies: raising water rates and restricting water use. However, each state and region could implement more complex forms of water policies. For example, various types of water conservation policies can be formulated by combining raising water rates and restricting water use (e.g., time of watering and the number of times of watering).

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Appendix A

A numerical example of comparing estimates from effect coding and dummy coding (unit: $).

Attributes	WTP with Dummy Coding	WTP with Effect Coding	WTP with Effect Coding Using Conventional Approach	WTP with Effect Coding Using Equation (6)
Shade tolerance	2	1	$2 \times 1 = 2$	$1-(-1) = 2$
40% water cost reduction	8	2	$2 \times 2 = 4$	$2-(-(2+4)) = 8$
50% water cost reduction	10	4	$2 \times 4 = 8$	$4-(-(2+4)) = 10$

Our example includes two attributes: Shade-tolerance with two attribute levels (yes, no) and Water cost reduction with three levels (no reduction, 40% reduction, and 50% reduction). In this example, the second and third columns present econometric estimation results from dummy coding and effect coding approaches, while the last two columns report interpretations of estimates with effect coding using conventional approach and Equation (6), respectively. For the attribute with two levels, the dummy coding approach indicates that consumers are willing to pay $2 more for the shade-tolerance attribute (because WTP for the base level is zero), which is the same as results from the effect coding approach using conventional approach, i.e., WTP with effect coding (in the third column) multiplied by 2 and Equation (6) (in the last column). In this case, all three procedures yield the same result. Note that for the effect coding approach with two levels, WTP for the base level is recovered by multiplying -1 to the WTP estimated econometrically (reported in the third column). However, when attribute levels are more than two, say three, the conventional approach can no longer be applied because the base-level WTP can be recovered by the negative sum of WTP for two attribute levels estimated econometrically. For example, for Water cost reduction, WTP for the base level, no reduction, is -6, i.e., $-(2+4)$. Therefore, WTPs for 40% water cost reduction and 50% water cost reduction estimated with effect coding and then calculated from the conventional approach differ from corresponding WTPs from the dummy coding approach, while a proper procedure, Equation (6), yields the same result with WTPs estimated from the dummy coding approach.

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