Consumers' Shares of Preferences for Turfgrass Attributes Using a Discrete Choice Experiment and the Best–Worst Method

Monika Ghimire^{1,4}, Tracy A. Boyer², and Chanjin Chung³

Department of Agricultural Economics, Oklahoma State University, Stillwater, OK 74078

Justin Q. Moss²

Department of Horticulture and Landscape Architecture, Oklahoma State University, Stillwater, OK 74078

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Abstract. This study compares preference shares of stress-tolerant, low-maintenance, and low-cost turfgrass attributes in five states (Florida, Georgia, North Carolina, Oklahoma, and Texas) in the southeastern and midsouthern United States using the discrete choice experiment (DCE) and the best–worst method (BWM). An online survey was conducted and a mixed logit model (MLM) was used to determine the homeowners' relative preferences for turfgrass attributes. The results of a survey of 1179 household consumers indicate that the most preferred attribute using either of the methods was low maintenance cost in all the states. Although the relative importance (preference share) by the DCE and the BWM for each attribute is statistically different, both methods yield a similar preference ordering for low-maintenance, drought-tolerant, and saline-tolerant turf, but a different ordering for shade-tolerant and low purchase–price turf. This study provides a framework for turfgrass researchers and producers to invest and expand outreach on desirable turfgrass attributes for homeowners.

The turfgrass industry is expanding rapidly as one of the fastest growing segments of agriculture sales in the United States due to its aesthetic benefits for residential and commercial properties (Haydu et al., 2006; Morris, 2003). The total value of turfgrass production in the five states in this study (Florida, Georgia, North Carolina, Oklahoma, and Texas) comprised \$404,821,402 in sales in 2012 (USDA-NASS, 2015). Apart from providing an aesthetically pleasing surface for outdoor activities, turfgrass is also used for

soil stabilization, water conservation, air and water filtration, and heat dissipation in urban areas. However, lawns occasionally create environmental externalities due to overuse of inputs like chemical fertilizer, pesticides and herbicides, high water use, and solid waste (Bormann et al., 2001).

A study by Milesi et al. (2005) found that three times more lawn is grown than any other irrigated crop in the United States, or ≈163,812 km², making turfgrass the largest irrigated crop in the United States. According to the U.S. Geological Survey, of the 26 billion gallons of water consumed daily in the United States, ≈7.8 billion gallons (30%) are devoted to outdoor uses, mainly landscaping (Solley et al., 1998; Vickers, 2001). About 40% to 75% of household water use is used for turfgrass irrigation in arid and semiarid regions (Ferguson, 1987; Mayer et al., 1999; Morris, 2003).

In the context of weather variability, climate change, drought, and reduced water supplies, lawn maintenance has become a challenge. During drought and water shortages, municipalities often prohibit the use of potable freshwater on the turfgrass landscape, considering it a low priority (Kjelgren et al., 2000). Many cities have imposed mandatory irrigation restrictions, water audits, water bans, and increased prices for potable water to minimize water scarcity during droughts and to meet long-term water

demand (Kenny et al., 2009). Thus, the shortage of freshwater or municipally treated water has compelled homeowners to use effluent or low quality water such as rainwater or reclaimed water for lawn irrigation purposes. Proper turfgrass management is also affected by several problems such as salinity, shade, winter stress, and high maintenance cost. The use of low quality water in hot and dry climates (drought conditions) may cause higher concentrations of salt in soil profile which not only adversely impacts turfgrass growth but also increases the maintenance cost. In addition, use of salt for road thawing in winter or intrusion of seawater in the coastal cities also increases the salinity problem in turfgrass (Murdoch, 1987). Furthermore, many home lawns have been adversely impacted by shade (Harivandi and Gibeault, 1996). Loss of turfgrass during winter due to freezing temperatures, termed as winterkill, is also another major problem of lawns (Frank, 2013). It is, therefore, necessary to develop more water-efficient and sustainable turfgrass cultivars that have wider geographical adaptability and are tolerant to several environmental stresses (drought, salinity, shade, and winterkill) to cope with environmental stresses and to better maintain turfgrass. This drives the demand for more innovative turf types that can tolerate stress and are economical to maintain (Yue et al., 2012). However, turfgrass breeders and producers desire more quantitative data on marketability of turfgrass traits to guide research in times of uncertain budgets (D. Martin, personal communication).

Determining consumers' preferences for product characteristics has gained increasing attention in decision-making and public policy. Prioritizing the importance for marketed agricultural goods is necessary to understand and manage the outcomes of research in publicly funded research in variety development. Developing and releasing a product depends on the desirability of the product to consumers compared with other products with similar characteristics, in this case, turfgrass, developed over years and decades of research. This current study of how consumers' prioritize several turf cultivars emphasizing shade, drought, winterkill, and saline tolerance in warm-season turfgrasses will help researchers focus on developing and marketing of highly desirable cultivars. Targeting research will maximize the benefit of publicly and privately funded turfgrass research and marketing efforts. Thus, the specific objective of this study is to identify the shares of preferences for stress-tolerant, low-maintenance, and low-cost turfgrass attributes from homeowners' perspectives in five states (Florida, Georgia, North Carolina, Oklahoma, and Texas) in the southeastern and midsouthern United States.

Public preferences for different products or the attributes of a product are usually elicited by direct or indirect valuation methods. Some of the most popular and relevant methods to elicit and rank consumers' preferences in

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¹Postdoctoral Fellow.

²Associate Professor.

³Professor.

⁴Corresponding author. E-mail: monika.ghimire@okstate.edu.

hypothetical scenarios are the DCEs and the ranking methods such as BWM (Bleichrodt, 2002). The DCE is a stated preference method which allows us to not only analyze consumers' preferences, but also to determine the shares of preferences of the attributes used in the experiment. The shares of preferences indicate the relative importance of the attributes used in the study ranging from 0 to 100 in percentage form. Shares of preferences for all the attributes total 100%. The shares of preferences of attributes can be determined by measuring the utility (part-worth) of attributes in various combinations of choices made (Louviere et al., 2000; Louviere and Woodworth, 1983). The BWM is a direct preference elicitation method that measures the subjective dimension, such as "degree of importance" or "degree of interest" (Auger et al., 2007). The BWM is a relatively simple method that yields coefficients for each attribute that can be used to determine the shares of preferences as the forecasted probability of the attributes.

Both the DCE (Cheraghi et al., 2008; Lancsar and Louviere, 2008; Ryan and Gerard, 2003) and the BWM (Flynn et al., 2007; Goodman et al., 2005; Lusk and Briggeman, 2009) have been widely used to determine the shares of preferences of attributes separately. Although some comparative DCE-BWM studies have been performed on the health technology sector (Potoglou et al., 2011; Whitty et al., 2014), there are few studies that focus on their relative performance in the agricultural sector goods like turfgrass, an essential component of many residential homes and always in demand. This study reports an empirical comparison of the DCE and the BWM using data collected from a survey conducted to elicit homeowners' values for different turfgrass attributes and compares the two methods directly using shares of preference for the turfgrass attributes in five states (North Carolina, Florida, Georgia, Oklahoma, and Texas) in the southeastern and midsouthern United States.

Materials and Methods

Homeowners survey

To determine the shares of preferences that homeowners place on the turfgrass attributes, we used standard design formats in the BWM and the DCE (Finn and Louviere, 1992; McFadden and Train, 2000). In both the DCE and the BWM, respondents were presented with a number of different profiles

of turfgrass attribute combinations. Attributes for the profiles were initially derived from a literature review on preferences of turfgrass attributes for lawns (Yue et al., 2012) and with consultation with a panel of breeders, physiologists, and other experts working in the turfgrass industry. Yue et al. (2012) used a choice experiment with real turf products to assess consumers' willingness to pay (WTP) for low input and aesthetic attributes of turfgrass. They reported that consumers' preferences and WTP are high for aesthetically pleasing and low maintenance attributes of turfgrass. Yue et al. (2012) were able to conduct a small group panel study with actual appearance. This study and the panel of experts chose to use a similar maintenance attribute and a different set of study-specific attributes including saline, winter, and shade tolerance to meet the funding objectives. The six turfgrass attributes [lost lawn area to winterkill, shade tolerance, watering your lawn (gallons/month), sod tolerance to salinity, maintenance and reoccurring costs (mowing, spraying, grooming, fertilizing, and weeding), and the total average purchase price for lawn of 5000 square feet and their corresponding levels] for the DCE were chosen after consultation with the expert panel and in collaboration with the Oklahoma State Turf Team (Table 1). The BWM attribute levels were simplified to represent the same attributes as in the DCE, by necessity of the difference in methods, the BWM attributes do not have corresponding levels of the DCE (Table 2).

A web-based online survey was conducted with homeowners from Florida, Georgia, North Carolina, Oklahoma, and Texas in Nov. 2013. Each survey included six BWM questions with each question containing three different options for different warm-season turfgrass attributes. The six DCE questions, each containing three different options, were followed by general and demographic questions. Respondents were asked to put themselves in the hypothetical position that they were buying turf for their lawns. A total of 1179 completed internet surveys programmed in Qualtrics using a convenience sample from Survey Sampling International were received.

Survey design

Discrete choice experiment. The experimental design for the DCE is similar to Louviere et al. (2000). Six measurable attributes associated with turfgrass adoption ranging from 2 to 4 levels were identified. A description of the attributes and

levels and the number of levels are provided in Table 1. These attributes and levels create $4^1 \times 3^3 \times 2^2 = 432$ possible combinations of attributes. However, a fractional factorial design that consists of 18 choice sets of turfgrass attribute profiles with a D-efficiency of 96.4% was used. Three surveys were created with each containing six different sets of the DCE choice set. Each DCE choice set had three different options (A, B, and C). Options A and B contained the combination of turfgrass attributes and its different levels (turfgrass attribute profiles), and option C represented the status quo or a no change option. For each choice set, respondents were asked to choose one of the three options. An example of the DCE choice set is provided in Fig. 1.

Best-worst method. Similar to the DCE, an experimental design method was used to create the set of the BWM choice sets. The balanced incomplete block design (BIBD) method was used with the six attributes of turfgrass (Table 2). The BIBD design focuses on the balanced design where the attributes appear an equal number of times and in equal proportion to all other attributes. The almost optimal BIBD was constructed using PROC FACTEX in SAS Software (SAS Institute Inc., Cary, NC) which is made up of six choice sets, with each containing three attributes. For the BWM task, participants were asked to choose their most and least important turfgrass attributes out of three attributes for their lawns. Each respondent's choice was coded as a 1 for each best-worst pair combination, and zero was coded for each possible pair not chosen. An example of the BWM choice set is provided in Fig. 2.

Econometric model. The MLM is used to determine the utility of each attribute of the turfgrass for both the DCE and the BWM. The MLM has different parameters for each respondent (Hensher and Greene, 2003; McFadden and Train, 2000), whereas the conditional logit model assumes that each respondent has the same parameters.

Discrete choice experiment. In the random utility theory, an individual i 's utility from choosing alternative j and choice set s is

$$U_{ij} = X_{ijs}\beta_{ijs} + \epsilon_{ijs} \quad (1)$$

where X_{ijs} is the vector of the turfgrass attributes that describes and represents the characteristics of alternative j , β_{ijs} is the parameter vector of the turfgrass attributes, and ϵ_{ijs} is the independent and identically distributed error term that follows a type I extreme value distribution. Allowing model

Table 1. Turfgrass attributes and levels for the discrete choice experiment.

No.	Attributes	Attribute levels	No. of levels
1	Lost lawn area to winterkill (50% probability)	0%, 20%, 40%	3
2	Shade tolerance	Yes, no	2
3	Watering your lawn (gallons/month)	Low (20,000 gallons), medium (40,000 gallons), high (60,000 gallons)	3
4	Sod tolerance to salinity	Yes, no	2
5	Maintenance and reoccurring cost (mowing, spraying, grooming, fertilizing, and weeding)	20% less than now, 20% more than now, no change	3
6	Total average purchase price for a lawn of 5,000 square feet (\$/ft ²)	\$0.20, \$0.40, \$0.60, \$0.80	4

parameters to vary randomly over individuals, the MLM is characterized by accommodating heterogeneity as a continuous function of parameters. The MLM incorporates unobservable heterogeneity by modeling a distribution of β_i as:

$$\beta_{ik} = \beta_k + \sigma_k \eta_{ik}. \quad (2)$$

The (relative) utility associated with each individual i for attribute k is represented in the DCE by a utility expression of the general form in Eq. (2), where η_{ik} is an error term with distribution $f(\eta_{ik})$. Hence, β_{ik} is a random variable with distribution $f(\beta_{ik})$, mean β_k , and standard deviation σ_k . The distribution function can take any form such as normal, lognormal, etc., which is chosen by the researcher. In this study, we use the normal distribution for all attributes. The

multidimensional integral does not have a closed form so that the probability can only be achieved with simulation, and parameters are determined by maximizing the simulated log likelihood function. The distribution simulation is based on 200 pseudorandom Halton draws.

In the DCE experiment, we can characterize the share of preference or relative importance for each attribute. This task can be done by considering how much difference each attribute could make in the total utility of a product (Orme, 2010). The difference is the range in the attribute's utility (part worth) values. The percentages from relative ranges are calculated, obtaining a set of attribute importance values that total 100%. The share of preference for each attribute is calculated as follows:

$$SP_k = \frac{\widehat{RN}_k}{\sum_{k=1}^6 \widehat{RN}_k} \quad (3)$$

where SP_k is the share of preference of the k^{th} attribute, and RN is the range of the utility coefficients for the attribute. Relative preference represents the magnitude of preference of an attribute which contributes to a consumer's valuation and purchasing decision. After the MLM is estimated, the estimated parameters are used as a prior and the person's actual choices from the DCE method are used as a posterior. The shares of preferences are estimated at the mean of Eq. (3) evaluated in 1000 random draws. The random draws following a normal distribution are generated using the estimated means and standard deviations of the MLM as in Eq. (2). This Bayesian calculation allows for a conditional distribution on a person's actual choice as discussed by Train (2003).

Best-worst method. Choosing the item that maximizes the difference in utility is a main assumption of the BWM. A choice set with T items, results in $T(T-1)$ tools or possible combinations of a set of best and worst items in a choice set. If λ_t is the location of the value t on the underlying scale

Table 2. Turfgrass attributes for the best-worst method.

No.	Attributes
1	Sod that is tolerant to drought
2	Sod that is tolerant to winterkill
3	Sod that is tolerant to shade
4	Sod that requires low average maintenance and reoccurring cost (like cost for mowing, spraying, grooming, and weeding)
5	Sod that is tolerant to salinity (salty soil or water)
6	Sod with low average purchase price (\$/ft ²)

Options 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
Lost lawn area to winter kill (50% probability)	40%	20%	If A or B were the only available options, I would not purchase new sod for my lawn
Sod tolerant to shade	Yes	No	
Watering your lawn (gallons/month)	Low (20,000 gallons)	High (60,000 gallons)	
Sod tolerant to salinity (salty water or soil)	No	Yes	
Maintenance and reoccurring cost (like mowing, spraying, grooming, fertilizing, and weeding, excluding purchase price)	No change	20% more than now	
Total average purchase price of sod for 5,000 square foot lawn (\$/ft ²)	\$0.20	\$0.40	

I would choose:

☐ **Option A**

☐ **Option B**

☐ **Option C**

Fig. 1. An example of the discrete choice experiment choice set.

If you were to buy sod/turfgrass for your lawn, please check your most preferred and least preferred

sod/turfgrass characteristic out of the following choices:

(Check only one that is most preferred and one that is least preferred.)

Most Preferred		Least Preferred
☐	Sod that is tolerant to salinity (salty water or soil)	☐
☐	Sod that is tolerant to winter kill	☐
☐	Sod that is tolerant to shade	☐

Fig. 2. An example of the best-worst method choice set.

of importance, then the true level of importance is $I_{it} = \lambda_i + \varepsilon_{it}$, where ε_{it} is an error term with an extreme value distribution (Finn and Louviere, 1992; Lusk and Briggeman, 2009). The probability that the consumer chooses to maximize the distance between items t and k , i.e., as the best and worst out of T items is the probability (i.e., difference in I_{it} and I_{ik}), is greater than all other $T(T-1) - 1$ possible differences in that choice set which takes a conditional logit form as follows:

$$\text{Prob}(t \text{ is most preferred and } k \text{ is least preferred}) = \frac{e^{\lambda_t - \lambda_k}}{\sum_{l=1}^T \sum_{m=1}^T e^{\lambda_t - \lambda_m}} - T \quad (4)$$

where m are the pair of attributes seen, but not chosen as the maximizing pair. The λ_i is estimated by maximum-likelihood estimation based on the probability statement in Eq. (4). That is, the dependent variable takes the value of 1 for the pair of attributes chosen by the consumer as best and worst, and a 0 for the remaining $T(T-1) - 1$ pairs of items in the choice set that were not chosen as best and worst. The estimated λ_i represents the importance of attribute T relative to some attributes that are normalized to zero to prevent the “dummy variable trap.” In the mixed logit form, the relative importance of each individual can be identified as:

$$\hat{\lambda}_{it} = \bar{\lambda}_{it} + \sigma_i \eta_{it} \quad (5)$$

where $\bar{\lambda}$ and σ are the mean and standard deviation of λ_i in the population, and η_{it} is the normally distributed random term with mean zero and unit standard deviation. Similar to the DCE, the BWM distribution simulation is also based on 200 pseudorandom Halton draws.

The share of preference for each attribute of turfgrass in the BWM can be calculated as the forecasted probability that each attribute is picked as the most important using the following equation:

$$\text{Share of preference for attribute } t = \frac{e^{\hat{\lambda}_t}}{\sum_{l=1}^T e^{\hat{\lambda}_l}} \quad (6)$$

Similar to the DCE, after the MLM is estimated, the estimated parameters are used as a prior and the person’s actual choices from the DCE method are used as a posterior. The share of preferences are estimated on the mean of Eq. (6) evaluated in 1000 random draws. The random draws following a normal distribution are generated using the estimated means and standard deviations of the MLM as in Eq. (5).

Comparing the share of preference in the DCE and the BWM. The shares of preference for each attribute obtained from the DCE and the BWM are compared by determining whether the difference in share of preference between two methods is statistically different. The preference ordering of the attributes between the two methods is also analyzed (i.e., which attribute is the most preferred and which is the least preferred within each method).

Data. The details of the demographic and household characteristics of the 1179 respondents from Florida, Georgia, Oklahoma, North Carolina, and Texas are shown in Table 3. The majority of the respondents are homeowners, and only households with lawns are included in this study. The demographics from the American Housing Survey for homeowners of the southern region were used to compare whether the demographics of this study are similar. Most of the demographics of this survey are representative of homeowners of the southern region of the United States. The median age of homeowners in the southern region is 55 years for 2013 (American Housing Survey, 2013). The median age of respondents across states in this study ranges from 50 to 56 years, with a standard deviation of ≈ 15 years. Likewise, the median household income for owner-occupied households is \$52,400 for the southern region (American Housing Survey, 2013). The mean annual household income in this study ranges from \$56,991 in Oklahoma to \$79,604 in Texas, which is comparatively higher than the regional data. The majority of the respondents are female in all states except for respondents from Oklahoma and Texas. Mean lawn sizes of the respondents range from 0.37 to 0.66 acres across states, indicating that respondents have a larger lawn size in general than may be common in the southern region. For example, the average lawn size in the United States varies from state to state, ranging from 0.06 acre in Washington, DC, to 0.51 acre in Georgia (Chapman, 2015).

Results and Discussion

Parameter estimates from the mixed logit

Discrete choice experiment. The estimates of the variables for the DCE are given in Table 4. Coefficient estimates have the expected signs for all significant attributes. Most of the variables are significant except for the average price variable in all states. In addition, the winterkill attribute is significant only in Oklahoma. The parameters are estimated for all states pooled together and for individual states. The joint likelihood ratio test indicates that each individual state is statistically different from the pooled data. These coefficient estimates are used to calculate the share of preference for each attribute for the homeowners.

The shares of preferences for the attributes using the DCE are provided in Table 5. Pooling all states together, the most preferred attribute for turfgrass is low average maintenance cost (53.6%), followed by shade-tolerant turf (22.8%), and water-conserving turf (18.8%). The least preferred attributes are low purchase price (0.1%), winterkill-tolerant turf (0.7%), and saline-tolerant turf (4.0%). The relative preferences of turfgrass attributes for lawns using the DCE among individual states are slightly different. However, in

each state, the three most preferred turfgrass attributes for homeowners are low average maintenance cost, shade tolerance, and water-conserving turf, whereas the least valued turfgrass attributes are low purchase price, winterkill tolerance, and saline tolerance. In Florida and Texas, low average maintenance cost is the most preferred attribute, followed by water-conserving and shade-tolerant turf. In Georgia, Oklahoma, and North Carolina, low average maintenance cost is the most preferred attribute, followed by shade-tolerant and water-conserving turf.

In all five states, low average purchase price is the least preferred attribute. Saline-tolerant turf is more preferred than winterkill-tolerant turf in Florida and Georgia, whereas winterkill-tolerant turf is more preferred than saline-tolerant turf in Oklahoma, North Carolina, and Texas. The share of preference for low-maintenance turf ranges from 42.4% (Georgia) to 59.1% (North Carolina). Shade-tolerant turf ranges from 16.5% (Florida) to 25.7% (Georgia), water-conserving turf ranges from 15.5% (Oklahoma and North Carolina) to 22.1% (Texas), saline-tolerant turf ranges from 1.2% (North Carolina) to 14.8% (Georgia), and the winterkill attribute ranges from 1.1% (Georgia) to 5.4% (Oklahoma). The share of preference for the average purchase price attribute is insignificant and less than unity for all states. Price is a small factor for overall replacement of lawn or sod installation, which could also be a reason of the insignificance of the average price variable in the model.

Best–worst method. In the analysis of the BWM, one variable (winterkill-tolerant turf) is dropped to avoid perfect collinearity in the variables. The parameter estimates of the BWM are provided in Table 6. Similar to the DCE, parameters of the BWM are estimated for all states pooled together and for individual states. The joint likelihood ratio test for the BWM also indicates that each individual state is statistically different from the pooled data. The parameter estimates of the BWM are used to estimate the share of preference of each attribute through forecasted probabilities as in Eq. (7). Pooling all states together, the most preferred attribute using the BWM is low average maintenance cost (44.9%), followed by drought-tolerant turf (25.8%), and low average purchase price (13.1%), whereas the least preferred attributes are saline-tolerant turf (6.4%) and shade-tolerant turf (9.8%) (Table 7). The drought tolerance attribute is the most preferred attribute in Texas, whereas low maintenance cost is the most preferred attribute in the other four states. The share of preference for low-maintenance turf ranges from 32.5% (Texas) to 50.6% (North Carolina), drought-tolerant turf ranges from 18.6% (Georgia) to 43.4% (Texas), low average purchase price of turf ranges from 9.7% (Texas) to 15.7% (North Carolina), shade-tolerant turf ranges from 7.3% (Florida) to 13.8% (Georgia), and saline-tolerant turf

Table 3. Summary of the demographics of the respondents.

States	Age (years)		Household income (\$)		Female (%)	Homeowners (%)	Lawn size (acres)	
	Median	SD	Mean	SD			Mean	SD
All states	51	15	67,455	48,033	53	98	0.52	0.45
Florida	56	15	65,693	48,612	38	97	0.37	0.35
Georgia	52	15	70,258	54,534	45	98	0.62	0.46
Oklahoma	52	14	56,991	38,713	61	97	0.57	0.49
North Carolina	54	14	67,624	49,770	46	99	0.66	0.47
Texas	50	14	79,604	45,073	38	99	0.39	0.36

Table 4. Parameter estimates for the discrete choice experiment (mixed logit).

Parameters	All states	Florida	Georgia	Oklahoma	North Carolina	Texas
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Lawn area lost to winterkill	0.001 (0.001) [−0.001] (0.053)	0.004 (0.003) [−0.001] (0.116)	0.001 (0.004) [−0.001] (0.105)	−0.005* (0.003) [−0.002] (0.089)	0.001 (0.003) [−0.001] (0.124)	0.003 (0.003) [−0.001] (0.105)
Shade tolerance	0.757*** (0.047) [0.006] (1.623)	0.767*** (0.119) [0.008] (4.004)	0.992*** (0.152) [0.051] (2.730)	0.888*** (0.121) [0.005] (3.203)	0.683*** (0.113) [−0.001] (3.915)	0.561*** (0.089) [−0.002] (3.394)
Water requirement (per 1,000 gallons)	−0.016*** (0.001) [0.0001] (0.034)	−0.024*** (0.004) [−0.0001] (0.075)	−0.016*** (0.003) [−0.001] (0.058)	−0.012*** (0.003) [−0.001] (0.070)	−0.012*** (0.003) [−0.001] (0.081)	−0.015*** (0.003) [0.0001] (0.073)
Saline tolerance	0.133*** (0.042) [0.009] (1.064)	0.410*** (0.115) [−0.009] (2.516)	−0.141 (0.155) [−0.788] (0.699)	0.158* (0.087) [−0.004] (2.064)	0.038 (0.101) [0.004] (2.53)	0.089 (0.085) [−0.001] (2.201)
Average maintenance cost	−0.021*** (0.002) [−0.072]*** (0.006)	−0.021*** (0.005) [0.107]*** (0.016)	−0.015*** (0.005) [0.065] (0.015)	−0.027*** (0.005) [−0.077]*** (0.013)	−0.025*** (0.005) [−0.073] (0.015)	−0.015*** (0.004) [0.052] (0.012)
Average purchase price	0.002 (0.091) [0.007] (0.801)	0.003 (0.002) [−0.001] (0.017)	−0.001 (0.002) [−0.0003] (0.020)	−0.001 (0.002) [−0.001] (0.015)	−0.002 (0.002) [−0.001] (0.020)	0.002 (0.002) [−0.001] (0.018)
Sample size	1,179	228	206	295	203	247
Log likelihood	−7,430	−1,414	−1,271	−1,835	−1,263	−1,572
Pseudo R ²	0.132	0.163	0.155	0.160	0.124	0.102

***and *represent significance at 1% and 10%, respectively. Numbers in parentheses () are SE and numbers in brackets [] are SD.

Table 5. Shares of preferences of attributes using part-worth of the discrete choice experiment.

Attributes	Share of preference					
	All states	Florida	Georgia	Oklahoma	North Carolina	Texas
Lawn area lost to winterkill	0.007 [0.007]	0.033 [0.016]	0.011 [0.008]	0.054 [0.028]	0.015 [0.012]	0.045 [0.024]
Shade tolerance	0.228 [0.100]	0.165 [0.069]	0.257 [0.095]	0.239 [0.101]	0.226 [0.114]	0.212 [0.087]
Water requirement (per 1,000 gallons)	0.188 [0.083]	0.208 [0.086]	0.161 [0.060]	0.155 [0.066]	0.155 [0.079]	0.221 [0.091]
Saline tolerance	0.040 [0.018]	0.088 [0.037]	0.148 [0.105]	0.043 [0.018]	0.012 [0.006]	0.034 [0.014]
Low average maintenance cost	0.536 [0.204]	0.505 [0.204]	0.424 [0.198]	0.510 [0.207]	0.591 [0.207]	0.488 [0.209]
Low average purchase price	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]	0.001 [0.001]

Numbers in brackets [] are SD.

ranges from 1.8% (Oklahoma) to 11.9% (Florida).

Different factors such as latitude, soil characteristics, water availability, and weather conditions naturally affect demand for turfgrass varieties by state which drives heterogeneity in preferences among states. All five states experience some sort of intermittent drought; Oklahoma and Texas were in a state of severe drought at the time of this study in 2013 (Svoboda, 2014; Fernando et al., 2015). Parts of North Carolina, Texas, and Georgia are subject to salinity. The importance of cold hardiness in North Carolina and Oklahoma are based on latitude, and the USDA cold hardiness zone as winterkill is an important

factor in these states in terms of bermudagrass and zoysiagrasses (D. Martin, personal communication).

Comparison of shares of preferences of attributes between the DCE and the BWM

A pairwise comparison of differences in the shares of preferences of turfgrass attributes between the DCE and the BWM is presented in Table 8. The results show that the preference levels by the DCE and the BWM are statistically different. However, out of the top three most preferred attributes using the DCE, two attributes (low maintenance cost and drought-tolerant turf) are also two of the most preferred attributes using the

BWM (Table 7). In Florida, Georgia, Oklahoma, and North Carolina, the most preferred attribute for homeowners using both methods is low-maintenance turf (Table 7). The most notable difference between the two methods is observed with the shade-tolerant turf and average purchase price attributes (Table 8). The difference is relatively high for these two attributes in each state. The shade-tolerant turf attribute is one of the highly valued attributes using the DCE, but it is one of the least preferred attributes using the BWM. In addition, the average purchase price is the least preferred attribute in the DCE, whereas it is mostly ranked the third valued attribute in the BWM. The possible reason for this might be due to insignificant parameter

Table 6. Parameter estimates from the best-worst method (mixed logit).

	All states	Florida	Georgia	Oklahoma	North Carolina	Texas
Parameters	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Shade tolerance	-0.055 (0.037) [0.796]*** (0.109)	0.268*** (0.219) [0.018] (1.925)	-0.188* (0.101) [-1.281]*** (0.256)	-0.255*** (0.095) [1.409]*** (0.221)	-0.373*** (0.104) [0.921]*** (0.275)	1.595 (0.193) [-1.418]*** (0.245)
Drought tolerance	1.0254*** (0.057) [0.941]*** (0.104)	1.225*** (0.116) [0.765]*** (0.218)	0.468*** (0.092) [0.610]*** (0.299)	1.272*** (0.146) [-1.191]*** (0.229)	0.479*** (0.102) [0.794]*** (0.276)	1.996*** (0.229) [-1.526]*** (0.259)
Saline tolerance	-1.369*** (0.071) [1.786]*** (0.111)	0.148* (0.083) [1.346]*** (0.184)	-1.826*** (0.218) [-2.097]*** (0.303)	-2.430*** (0.225) [1.504]*** (0.241)	-1.923*** (0.235) [2.080]*** (0.313)	-1.334*** (0.165) [1.979]*** (0.277)
Low average maintenance cost	1.593*** (0.080) [-1.340]*** (0.109)	2.131*** (0.185) [-1.246]*** (0.216)	1.479*** (0.182) [-1.652]*** (0.280)	1.663*** (0.178) [1.697]*** (0.243)	1.758*** (0.216) [-1.595]*** (0.287)	1.595*** (0.192) [-1.417]*** (0.254)
Low average purchase price	0.413*** (0.037) [0.485]*** (0.148)	0.842*** (0.088) [-0.585]*** (0.249)	0.292*** (0.083) [-0.386] (0.399)	0.174*** (0.084) [-1.002]*** (0.233)	0.328*** (0.093) [-0.739] (0.288)	0.475*** (0.091) [-0.571] (0.351)
Sample size	1,179	228	206	295	203	247
Log likelihood	-14,076	-2,821	-2,491	-3,191	-2,342	-2,889
Pseudo R^2	0.47	0.43	0.45	0.59	0.51	0.51

***, **, and *represent significance at 1%, 5%, and 10%, respectively. Numbers in parentheses () are SE and numbers in brackets [] are SD.

Table 7. Shares of preferences of attributes using the best-worst method.

Attributes	All states	Florida	Georgia	Oklahoma	North Carolina	Texas
Shade tolerance	0.098 [0.096]	0.073 [0.043]	0.138 [0.158]	0.105 [0.144]	0.093 [0.103]	0.093 [0.112]
Drought tolerance	0.258 [0.197]	0.219 [0.163]	0.186 [0.144]	0.313 [0.252]	0.187 [0.156]	0.434 [0.287]
Saline tolerance	0.064 [0.116]	0.119 [0.147]	0.062 [0.129]	0.018 [0.038]	0.056 [0.117]	0.052 [0.109]
Low average maintenance cost	0.449 [0.262]	0.451 [0.258]	0.464 [0.283]	0.441 [0.302]	0.506 [0.287]	0.325 [0.263]
Low average purchase price	0.131 [0.098]	0.138 [0.101]	0.149 [0.116]	0.123 [0.140]	0.157 [0.140]	0.097 [0.096]

Numbers in brackets [] are SD.

Table 8. Differences in share of preferences for attributes between the discrete choice experiment (DCE) and the best-worst method (BWM).

Attributes	All states	Florida	Georgia	Oklahoma	North Carolina	Texas
	DCE-BWM	DCE-BWM	DCE-BWM	DCE-BWM	DCE-BWM	DCE-BWM
Shade tolerance	0.130**	0.092**	0.119**	0.134**	0.133**	0.119**
Drought tolerance	-0.070**	-0.011**	-0.025**	-0.158**	-0.032**	-0.213**
Saline tolerance	-0.024**	-0.031**	0.086***	0.025**	-0.044**	-0.018**
Low average maintenance cost	0.087**	0.054**	-0.040**	0.069**	0.085**	0.163**
Low average purchase price	-0.130**	-0.137**	-0.148**	-0.122**	-0.156**	-0.096**

**Represents significance at 5% level. A pairwise t test shows a significant difference between two methods.

estimates for the average purchase price attribute in the DCE. In Texas, the difference in the share of preference for the drought tolerance attribute is high as the respondents value the drought tolerance attribute more in the BWM, whereas the low maintenance cost attribute is valued more in the DCE (Table 7). Though the shares of preferences are statistically different between the two methods, the ordering in the shares of preferences is similar except for the average purchase price and shade-tolerant turf attributes (Table 8). Previous studies have reported similarities (Potoglou et al., 2011) as well as differences in estimates of attributes from these two methods (Whitty et al., 2014). Similar to this study, Whitty et al. (2014) also reports differences between the two methods, but a similar ordering of the attributes.

Homogeneity in shares of preferences of the attributes among states and the larger R^2 in this study indicate that the BWM could be

a better method to elicit relative preferences for attributes of a product. However, the variances of attributes for most of the variables in the DCE are lower compared with the BWM, which might support the use of the DCE. Thus, there is no clear indication of one method being better than the other. Some studies argue that the BWM is preferable as there is only one option to choose either the “most” or “least” preferred, and there is a lower probability of bias in the rating scale (Cohen and Markowitz, 2002). However, studies also suggest that the DCE is a more feasible and reliable method to elicit the preferences, since the BWM becomes complicated due to the difficulty of making the shift among attributes while choosing the best and worst options (Xie et al, 2012).

Summary and Conclusions

This study compares the shares of preferences of stress-tolerant, low-maintenance,

and low-cost turfgrass attributes using the DCE and the BWM in five states (Florida, Georgia, North Carolina, Oklahoma, and Texas) in the southeastern and midsouthern United States. An online survey among homeowners was conducted, and the MLM was used for analysis of both methods to determine the relative preference of turfgrass attributes for the homeowners. The results of a survey of 1179 household consumers indicate that the most preferred attribute using either of the methods is low maintenance cost in all the states. Although the shares of preferences by the DCE and the BWM are statistically different, both methods yield a similar preference ordering for attributes such as low-maintenance, drought-tolerant, and saline-tolerant turfgrasses. However, the preference ordering for shade-tolerant turf and low-priced turf is different in the two methods. In the context of this study, the DCE could be a more appropriate gauge of the market for use by turf wholesalers due to

the inclusion of an actual price variable and the respondents' ability to indirectly choose an option and make a trade-off among a set of scenarios. In addition, the BWM may not perform well in a priority setting context for applied marketing studies (Whitty et al., 2014). However, the ambiguity about methods warrants further study about the selection of the best method. The large standard deviations in the shares of preferences of attributes indicate that there is heterogeneity in the relative importance of turfgrass attributes.

Overall, this study provides an early insight into the use of preference share scales to rank the stress-tolerant, low-maintenance, and low-cost turfgrass attributes. This study gives a notable outcome in reconfirming the findings from Yue et al. (2012) that people value low-maintenance turf the most using both methods. In addition, drought-tolerant and shade-tolerant turf are also high on the homeowners' priority list. Thus, this study provides framework for the warm-season turfgrass researchers and producers to invest and expand outreach on desirable turfgrass attributes for the homeowners.

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