ESSAYS ON RESIDENTIAL WATER DEMAND AND CONSUMER PREFERENCES FOR TURFGRASS ATTRIBUTES

By

MONIKA GHIMIRE

Bachelor of Science in Environmental Management
Pokhara University
Kathmandu, Nepal
2008

Master of Science in Agricultural Economics
Oklahoma State University
Stillwater, Oklahoma
2012

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
July, 2015

ESSAYS ON RESIDENTIAL WATER DEMAND AND CONSUMER PREFERENCES FOR TURFGRASS ATTRIBUTES

Dissertation Approved:

Dr. Tracy Boyer

Dissertation Adviser

Dr. Chanjin Chung

Dr. Jayson Lusk

Dr. Justin Q. Moss

Outside Committee Member

ACKNOWLEDGEMENTS

I especially thank my major advisor, Dr. Tracy Boyer, for her excellent guidance, encouragement, patience, and support during my research and study at Oklahoma State University. I would like to thank Dr. Chanjin Chung, Dr. Jayson Lusk, and Dr. Justin Q. Moss for serving on my committee. I am thankful to the Department of Agricultural Economics and Department Head, Dr. Mike Woods, for providing me the opportunity to continue my studies and research at Oklahoma State University.

I would like to thank my husband, Dr. Pradeep Wagle, for his support, guidance, encouragement, quite patience, and unwavering love. My deepest gratitude goes to my family members for their unflagging love and support throughout my life. I offer my regards and blessings to all of those who supported me in any respect during the completion of my program.

Name: MONIKA GHIMIRE

Date of Degree: JULY, 2015

Title of Study: ESSAYS ON RESIDENTIAL WATER DEMAND AND CONSUMER PREFERENCES FOR TURFGRASS ATTRIBUTES

Major Field: AGRICULTURAL ECONOMICS

Abstract: The first essay determined the residential water demand and the factors affecting water demand for different periods (pre-drought vs. during-drought and summer vs. winter) in Oklahoma City area. Individual household water consumption, household age, household value, parcel size, water price, and weather variables from July 2009 through December 2012 for Oklahoma City area were used. A two-stage least-squares estimation with an instrumental variable was used to develop a water demand model. Results indicated that water demand was inelastic to water price except for high consumption period. Parcel size, income, and temperature were positively related to water demand, while rainfall, household age, and water price negatively influenced water demand.

The second essay determined the consumers' preferences and willingness to pay for different turfgrass attributes while assessing the heterogeneity in preferences for attributes of turfgrass in five states (Florida, Georgia, Oklahoma, North Carolina, and Texas) of the U.S. Results based on a survey of 1,179 household consumers indicated that there was significant preference heterogeneity for the preferences of turfgrass attributes. The household turf consumers were clustered in two broad classes; "*willing household consumer*" and "*reluctant household consumer*". Willing household consumers were characterized by high income and hobbyist, while reluctant household consumers were characterized by people more than 45 years. Results also indicated that willing household consumers were most likely to pay more for improved turfgrass attribute than were reluctant household consumers.

The third essay determined the preference shares for the turfgrass attributes and compared and contrasted the results from the discrete choice experiment (DCE) and best-worst method (BWM). An online survey was conducted and a mixed logit model was used to determine the homeowners' relative preferences for turfgrass attributes. The results indicated that the most preferred attribute using either of the methods was low maintenance cost. Although the relative importance by the DCE and the BWM were statistically different, both methods yielded a similar preference ordering for low maintenance, drought tolerant, and saline tolerant turf, but different ordering for shade tolerant and low purchase price turf.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

PREFACE

Oklahoma experienced one of the driest periods on record from September 2010 through April 2014. The year 2012 was Oklahoma's warmest year on record (Oklahoma Mesonet, 2013a). Approximately 9% of the United States (U.S.) freshwater withdrawals is devoted to household water usage. However, as a result of a local and regional drought, water supplies are constrained for multiple uses including lawn irrigation which comprises 50-70% of household water demand.

Effective municipal water usage during prolonged droughts has been a major issue in water management policy in the U.S. Understanding municipal water demand during these periods and promoting water conserving turfgrass that has wider geographical adaptability to climate and soil variability are vital for preserving water availability in many municipalities. This dissertation is composed of three papers designed to determine residential water demand and consumer preferences for improved turfgrass attributes.

The first paper (Chapter I) used spatially explicit household data to determine the residential water demand in Oklahoma City area for pre- and during-drought periods, and for seasonal consumption periods. This study determined the price and income elasticity of residential water demand under uniform volumetric water pricing. The study also compared the elasticity of both marginal and average pricing for pre- and during-drought periods and seasonal low and high water consumption periods. Results indicated that increases in water price had a very small effect on reducing water demand and the effect was minimal during-drought.

The second paper (Chapter II) determined consumers' preferences and willingness to pay for drought, shade, winterkill, and salinity tolerant and low maintenance attributes of turfgrass, while assessing the heterogeneity in their preferences for these turfgrass attributes. The results indicated that there was considerable preference heterogeneity among the household turf consumers. Household turf consumers were clustered in two classes; "*willing household consumer*" and "*reluctant household consumer*". Willing household consumers were characterized by high income and hobbyist while reluctant household consumers were characterized by people of age over 45 years. Results also suggested that willing household consumers were likely to pay more for most turfgrass attributes than reluctant household consumers.

The third paper (Chapter III) examined preference shares of the abiotic stress tolerant (drought, shade, winterkill, and salinity) and low maintenance attributes of turfgrass and compared and contrasted the results from the discrete choice experiment and the best worst method. The results indicated that the most preferred attribute using either of the methods was low maintenance cost. Although the preference shares for the turfgrass attributes between two methods were statistically different, the directions of preference ordering were similar for two methods except for shade tolerant and average purchase price attributes.

CHAPTER I

ESTIMATION OF RESIDENTIAL WATER DEMAND UNDER UNIFORM VOLUMETRIC WATER PRICING

ABSTRACT

Understanding the factors affecting residential water demand is critical to implement and improve water management policies during the extreme climate conditions such as drought. As few studies relating water demand to uniform volumetric water pricing exist, this study aims to determine the price and income elasticity of residential water demand under uniform water pricing. Second, this study compares the elasticity of both marginal and average pricing for pre- and during-drought periods and seasonal low and high consumption periods. Individual household water consumption, household age, household value, parcel size, water price, and weather variables from July 2009 through December 2012 for Oklahoma City area were used. A two-stage least-squares estimation with an instrumental variable is used to develop a water demand model. Results indicate that water demand is inelastic to water price except for high consumption period. Parcel size, income, and temperature are positively related to water demand, while rainfall, household age, and water price negatively influence water demand. This study provides important insight into major variables affecting water demand using easily obtained data.

Introduction

Interest in efficient use of water resources has been growing as municipalities face variability in water supply and increasing demands for residential water. Several factors such as weather, water pricing, and household demographics and characteristics influence residential water demand. Moreover, water demand also shows seasonality (demand varies with the seasons of the year, the day of the week, or the hours of the day) due to changes in weather conditions (Arbués et al., 2003). Understanding the effects of determinants such as price, household characteristics, and demographics on water demand is necessary to develop effective domestic water supply management policies. An essential management needs is to better understand and predict how water demand changes seasonally and during drought conditions (Kenney et al., 2008; Rockström, 2003).

Oklahoma has experienced one of the driest periods on record since September 2010 with the arrival of La Niña in the equatorial pacific waters (Cole and Leslie, 2011). The year 2012 was Oklahoma's warmest year on record (Oklahoma Mesonet, 2013a). In addition, Oklahoma has also experienced increasing variability in rainfall and temperature over the years, which extensively influences water demand. This makes the study of specific seasonal and drought period water demands relevant in Oklahoma.

Although residential water demand has been a topic of research in the past, it has not been analyzed for Oklahoma City, OK. The Oklahoma City Utilities Department provides water to the people of Oklahoma City, OK and other municipalities in the Oklahoma City metropolitan area. Treated municipal water serves several different use categories including residential, agricultural, industrial, and commercial. Residential water demand includes water used by households for indoor activities including cooking, bathing, and washing, and outdoor activities like landscape irrigation and recreation. According to water industry estimates, an average person uses about 3,000 gallons (11,355 m^3) of water per month (City of Oklahoma City, 2013a).

Several studies have estimated water demand and price elasticity of the demand (Gaudin et al., 2001; Hewitt and Hanemann, 1995; Kenney et al., 2008; Michelsen et al., 1999; Nieswiadomy and Molina, 1989). However, most of the previous studies were based either on flat rate pricing or increasing/decreasing block rate pricing structures. Although uniform volumetric pricing for water was/is in practice in several cities (such as Oklahoma City, Chicago, Memphis, Indianapolis, Baltimore, New York etc.), limited studies exist that are based on uniform volumetric pricing of water (Hoffman et al., 2006 and Olmstead et al., 2007). Uniform volumetric pricing is different from flat rate pricing. A uniform volumetric pricing schedule is metered and combines a monthly fixed base service charge with a constant volume charge for the amount of water consumed by the households, measured in 1000 gallons increments (3.79 m^3). By contrast, flat rate pricing is unmetered and a fixed charge is paid for an unlimited amount of water consumed by each household.

Hoffman et al. (2006) modeled water demand in Brisbane, Australia using marginal price and they found that price and income elasticities of water demand were inelastic. While Olmstead et al. (2007) assessed water demand model comparing increasing block rate pricing with uniform volumetric pricing and found that price elasticity varies with difference in pricing structure. Both of these studies uses marginal price as price vehicle. The current study extends the residential water demand model under the uniform volumetric pricing for both average and marginal pricing structures and also assessed the change in elasticity in different periods (pre-drought versus during-drought and summer-fall high consumption period (HCP) versus winter low consumption period (LCP)) using individual household level data. Thus, the general objectives of this study are to estimate water demand while assessing different factors affecting water demand and to determine price and income elasticity of demand under the uniform volumetric pricing structure of water. The specific objective of this study is to identify the variation in price and income elasticity of water demand and other variables pre- versus during-drought and in the HCP versus the LCP while using average and marginal pricing of water.

Methodology

Theoretical Review

The consumer equates the marginal or average price of water to the benefit of water consumption in order to determine the quantity of water consumed. The other variables affecting consumer choice may include household size and structure, and weather variables like rainfall and temperature (Arbués et al., 2003).

Water price is a major factor in controlling water demand. In most cases, water demand is estimated as inelastic since water has no substitutes for basic uses and consumers show a low level of awareness of the rate structure because water bills are only a small proportion of most household's income (Chicoine and Ramamurthy, 1986). Water pricing provides an obvious mechanism for water utilities to strategically change consumers' behavior. Demand management is highly influenced by price, whether the price is inelastic or elastic. Water demand is analyzed to test the hypothesis that customers respond to increases in both average and marginal prices of water as found in previous studies (e.g. Gaudin et al., 2001; Hewitt and Hanemann, 1995; Kenney et al., 2008). Previous studies used either average price (Gaudin et al., 2001; Kenney et al., 2008; Michelsen et al., 1999) or marginal price

(Nieswiadomy and Molina, 1989) to study the pricing effect on water demand. However, extensive discussion has occurred in the literature on pricing structure (Nataraj and Hanemann, 2011; Schleich and Hillenbrand, 2009) and whether consumers respond to the marginal prices or the average water price. An informed consumer may respond to the marginal price, while consumers with incomplete information about water pricing may react to the average price. Effects of both prices on water demand are compared in this study.

In water demand studies, climatic effects have been used in various ways. For example, rainfall during the growing season (Foster and Beattie, 1979), evapotranspiration and rainfall (Billings, 1982), monthly average temperature, summer rain, and rise in temperature beyond 57 ºF (14ºC) (Billings, 1987), and temperature together with annual rainfall (Stevens et al., 1992) have all been used. Weather conditions can impact short term water demand decisions for uses such as landscape irrigation. Therefore, weather variables are also used as the explanatory variables for affecting water demand in this study. Hot-dry weather is expected to increase water demand compared to cold-wet weather conditions. Across the municipalities of Oklahoma, July and August are the maximum domestic water usage months (Moss et al., 2013). In these months water consumption is high, especially for lawn irrigation (Figure. 1.1). Consumption refers to the actual volume of water used and serves as a dependent variable for estimating the water demand models.

The unavailability of demographic information for individual households is a limitation for assessing the impact of variability on household water demand. Current research suggests that household water demand is influenced by heterogeneity in households due to differences in wealth, income, and parcel size. The assessed value of the property is also occasionally used as a proxy variable for income in household-based studies (Dandy et al., 1997) because it is highly correlated with income (Lyman, 1992). Jones and Morris (1984) used a proxy for family income based on educational level, car ownership, assessed property value, and the age of the residence to avoid a correlation problem. An increase in parcel size corresponds to an increase in lawn size and summer water demand since 50 to 70 percent of city water production is used to irrigate lawn during the summer months in the United States (Kjelgren and Farag, 2002; Mayer and DeOreo, 1999). Houses built after 1994 have low-flow toilets and showers, as the U.S. Energy Policy Act of 1992 restricted household toilets to 1.6 gallons (0.006 m^3) per flush (Rockaway et al., 2010). All shower and faucet fixtures manufactured in the United States since 1994 are regulated to have a maximum water flow at or below 2.2 gallons (0.008 m^3) per minute. Fixture water use, as measured by pre and post regulation date of house construction, affects household water demand.

Data

Study Area. The study area is the Oklahoma City metropolitan area, a large urban region in the central part of the state of Oklahoma. Oklahoma City is the capital city of Oklahoma and is a rapidly growing city and a metro-area with a population of 1.25 million, an increase of 8.1 percent since 2000 (Census 2010). The City of Oklahoma City Water Utilities Trust (OCWUT) is responsible for supplying water for Oklahoma City and the surrounding communities. The OCWUT currently serves approximately 600,000 municipal, domestic, and industrial water customers with a current demand of 241,768 acre-feet (298 Mm^3) per year. Based on our analysis of billing records from 2009 through 2012, 50-60 % of total treated water is supplied to residential consumers, mostly single family homes. Monthly water consumption for 10,000 randomly selected residential households is used in this study. The monthly water consumption data was obtained from the OCWUT. The monthly average residential water consumption from July 2009 through December 2012 is presented in Figure. 1.1

Household Characteristics. Lack of individual residence data is a major obstacle in determining the impact of household characteristics on residential water demand. Based on the literature to date, the major household characteristics affecting residential water demand are household income, wealth, family size, lawn size, household value etc. (Cavanagh et al. 2002; Jones and Morris 1984; Kenney et al. 2008; Lyman 1992; Renwick and Green 2000; Syme et al. 2000). This study used GIS referenced billing data to identify house assessed value, year constructed, and parcel size. The house value, parcel size, and the year constructed data were obtained from OCWUT, which was constructed by them from the assessor databases for the Oklahoma City metropolitan area. The assessed value of the household for 2011 is used as a proxy for an income variable because of the high correlation between them.

Pricing Structure. Water pricing for Oklahoma City customers is structured based two categories: a base service charge and a constant per unit volume charge. The base service charge is the fixed price charged to individual households according to the meter size. The unit use charge is the price charged to households based on the volume of the water usage and is the marginal price paid for every 1000 gallons ($3.79m^3$) of water usage. A sum of the base service charge and the total use charge is billed to the customers as the water charge. The base service fee and use charge (per 1000 gallons or 3.79 m^3) change annually. The base service fee and unit use charge have been increasing annually by approximately 6% and 5%, respectively (Table 1.1). The monthly average price was estimated utilizing both water and sewer charges in this study.

Weather Conditions. Temperature and rainfall patterns for Oklahoma City area were obtained from Oklahoma Mesonet (Mesonet, 2013) and calculated for monthly periods from July 2009 through December 2012. The Oklahoma Mesonet, a joint project of Oklahoma State University and the University of Oklahoma, is a network of over 100 Mesonet automated weather stations across the state of Oklahoma (Brock et al. 1995). The Oklahoma City area receives about 35 inches (889 mm) of annual rainfall on average and rainfall is light and unreliable in the summer months (Oklahoma Mesonet 2013b). The area received a similar amount of average annual rainfall (36.8 inches or 934.7 mm) in 2010. However, the years 2011 and 2012 were drier than average, with annual rainfall 23% below the 30-year average in 2011 and 10% below in 2012. The summer of 2012 was slightly wetter than the summer of 2010, but summer of 2011 was excessively drier (Figure. 1.1).

Procedure

A basic condition for unbiased and consistent parameter estimation under ordinary least squares (OLS) is that there is no correlation between the error term and any of the explanatory variables. Using the average price in the water pricing model for demand estimation generates a simultaneity problem because the average price is determined by the consumed quantity of water and marginal price, therefore, will be correlated with the error term and the OLS estimation leads to biased and inconsistent results. Thus, the two-stage least squares (2SLS) method is applied using instrumental variables as in the previous studies (Kenney et al. 2008; Michelsen et al. 1999; Nieswiadomy and Molina 1989). In the first stage of this method, the endogenous variable is regressed on a set of instrumental variables that are not correlated with the error term but are highly correlated with the endogenous variable itself. The average water price is regressed against all the explanatory variables and instrumental variables: the regional gas price (Energy Information Administration 2015) and the consumer price index (Bureau of labor Statistics 2015) in equation (1). The average price equation with instrumental variables can be expressed as follows:

$$\ln(P_{it}) = \beta_0 + \beta_1 \ln(Income_i) + \beta_2 \ln(ResSize_i) + \beta_3\, Maxtemp_t + \beta_4\, TotPrcp_t + \beta_5 Yrbuilt_i + \beta_6 \ln(GP_t) + \beta_7 \ln(CPI_t) + \epsilon_{it} \quad (1)$$

where P_{it} is the average price of water consumption in dollars in households *i* (*i*=1,…,10,000), month *t* (*t*=1,…,42) from July 2009 through December 2012, *ResSize* is household area, *MaxTemp* is the maximum monthly temperature, *TotPrcp* represents total monthly rainfall, *GP* is the regional gas price, CPI is the regional consumer price index, *Yrbuilt* is the indicator variable which is equal to 1 if the house was built after 1994 and 0 if it was built before 1994, β's are the parameter estimates of the variables, and ϵ_{it} is the error term.

A monthly regional gas price and consumer price index are introduced as instrumental variables as they are correlated with average water price and exogenous to water demand. The predicted value of average price at first stage is then used in the second stage, in an OLS regression, as an explanatory variable in place of the endogenous average price variable.

The demand model is conceptually similar to previous studies which assume that household water demand is a function of price, weather, and household characteristics like income, parcel size, and the year constructed. The following model was used in this study:

$$\ln(Q_{it}) = \beta_0 + \beta_1 \ln(P_{it-1}) + \beta_2 \ln(Income_i) + \beta_3 \ln(ResSize_i) + \beta_4\, Maxtemp_t + \beta_5\, TotPrcp_t + \beta_6 Yrbuilt_i + \gamma_i + \varepsilon_{it} \quad (2)$$

where Q_{it} is the total amount of water consumed in households. P_{it-1} is the lagged predicted average water prices from first stage (for average price model)/marginal water price (for marginal price model), γ_i is household random effect. In a household, the price of the previous month's water bill is paid at the beginning of current month which influences the next or current month's water demand.

The variable definitions and summary statistics are provided in Table 1.2. The demand model is estimated to investigate the variability of the model for all billing periods: (July 2009 through December 2012), pre-drought (July 2009 through August 2010) and during-drought (September 2010 through December 2012) periods, and the LCP (January through May and October through December) and the HCP (June through September) separately. The model is also estimated for both average and marginal price signals. The 2SLS model is used for all periods for an average price model while for the marginal price model only the OLS estimation is done since there was no likelihood of simultaneity among marginal price and water demand. Due to the log-log relationship between demand, and price and income, the coefficient estimate on price and income in the model gives the price and income elasticity of water demand directly.

Results and Discussions

The parameter estimates of the variables in equation (2) using the average price for all billing periods, pre- and during-drought billing periods, and the HCP and LCP models are provided in Table 1.3. The parameter estimates for all billing periods, the HCP, and the LCP using marginal price are provided in Table 1.4. Pre- and during-drought variability in the marginal price model was not estimable as the marginal price varied by year only.

The water demand model in this study yielded the expected signs for most of the variables along with statistical significance ($P < 0.1$) for all explanatory variables in equation (2). The adjusted R^2 value is ~0.16 for all billing, pre-drought and during-drought periods, and it ranged from 0.03 to 0.08 for the HCP and the LCP respectively (Tables 1.3 and 1.4). These R^2 values are relatively low, but the significant estimates describe some relationship between water demand and explanatory variables. Other water demand studies using simultaneous equations showed low R^2 values ranging from 0.07 to 0.50 (Hewitt and Hanemann 1995; Michelsen et al. 1999; Nieswiadomy and Molina 1989; Schleich and Hillenbrand 2009). A low R^2 could be the result of omitted variables that affect demand that are unknown such as conserving or wasteful behaviors, the actual number of household residents, and the use of proxy variables for unknown variables such as fixture type and actual income.

Most of the estimated parameter coefficients has the similar magnitudes for both the marginal and the average price models for all billing periods, pre-drought and during-drought periods, and the HCP and LCP models except price elasticity and rainfall. Price elasticity is more elastic for the average price model, compared to the marginal price model. The price elasticity of water demand is inelastic for the all billing periods for both average and marginal price models. For the average price model, the price elasticity of water demand is -0.38 for all billing periods (Table 1.3), while for the marginal price model, price elasticity is -0.66 (Table 1.4), consistent with the findings of previous studies. Brookshire et al. (2002) reported that the price elasticity of water demand is in the range of -0.11 to -1.59 with an average of -0.49. Espey et al. (1997) in a meta-analysis of 24 studies reported that elasticity ranged from -0.02 to -0.75.

Pre-drought and during-drought period price elasticities of water demand are also inelastic. People are expected to be less responsive to increases in price during a drought period, which is reflected by the average price estimate for the during-drought period model. The average price elasticity is more elastic in the during-drought period (-0.49) compared to the time range of the pre-drought period (-0.67). Price elasticity of water demand shows a similar pattern in the HCP for both the average and the marginal price models. In the HCP, both the average price and the marginal price estimates re positive and did not reduce water demand. Both the marginal and the average price elasticities for water demand are very elastic in the HCP compared to the LCP. These results indicate that an increase in price has a very small effect on water demand and that the effect is minimal during drought and the HCP (June, July, August, and September).

The income elasticity of water demand is positive, highly significant, and less than unity during all periods for both the average and the marginal price models. This suggests that residential water is a necessity for households (Table 1.3 and Table 1.4). As expected, income elasticity of demand is more elastic in the during-drought period compared to the pre-drought period and during the HCP compared to the LCP. Likewise, the coefficient for parcel size is also positive and highly significant for all periods, indicating that an increase in the size of a parcel increases water demand. The parameter estimates show that households built after 1994 are likely to consume less water. These results are also consistent with the results of previous studies (Cavanagh et al. 2002; Hewitt and Hanemann 1995; Nieswiadomy and Molina 1989; Renwick and Green 2000). A higher coefficient estimate on parcel size in the HCP compared to the LCP indicates that higher water demand may be related to lawn irrigation.

Intuitively, demand for water increases if the temperature increases, and decreases if there is more rainfall. Both models (average and marginal price) predicts that water use increased by about 1% for a 1°F (0.56 °C) increase in average daily maximum temperature over all periods. Similarly, for every additional inch (25.4 mm) of rainfall, water demand decreased approximately by 1% for all billing period. In this study, the weather estimates have the expected signs for all periods in both models (average and marginal price) except during the drought period and the LCP. The positive estimates for rainfall during-drought period and the LCP indicate that the water demand do not decrease during these periods. Several reasons might be responsible for this finding. Residents may irrigate lawns to maintain them during drought conditions due to increased evapotranspiration rates or they might have used more water for bathing and/or swimming. Similarly, during the LCP rainfall might not be enough to influence the water demand. However, further research is required to better understand the relationship between water demand and major determinants of water consumption during severe weather conditions.

Summary and Conclusions

Although the parameter estimates are similar for both the average and the marginal price models, the average price model showed a somewhat better fit (adjusted R^2) for most of the billing periods. The average price elasticity is more inelastic and highly significant compared to the marginal price elasticity for all billing periods. Although the average price model gives better predictions for water demand, more research is required to confirm that the average price is a better price measure than the marginal price.

The results indicate that price increases have very small effect on reducing water demand and the effect is minimal during-drought and during the HCP which are more inelastic in these periods. Income elasticity is consistently less than unity and statistically significant over each period for both the average price and the marginal price models. Water demand decreases if the house was constructed after 1994 and increases as the parcel size increase. Since parcel size indicates the lawn size, our findings suggest a need for outdoor watering education to decrease wasteful irrigation, especially during the HCP. Xeriscaping subsidies for water conserving landscapes may also be a viable option. Parcel size is also readily observable in tax assessment data, allowing agency targeting of consumers by utilities facing supply restrictions. All other variables like temperature and house year built are statistically significant and have the expected signs. However, rainfall estimates has a positive effect on water demand during the drought and the LCP. This may be for bathing/swimming or for maintaining the lawns during the drought period. Rainfall during the drought and the LCP also do not eliminate the rain deficit for turf needs. However, more research using plant required water and evapotranspiration from remotely-sensed satellite data is to be matched with this household level data in the future to confirm adequate required irrigation in the high consumption periods.

This study provides insight into the major variables that affect water demand. In the range of the unit water prices of \$2.26 to \$2.55 per 1000 gallons (3.79 m^3) during the study period, water demand is mostly inelastic. However, a combination of price increases and education could lead to increased adoption of water conserving summer practices. Uniform volumetric pricing do not show variability between lower and higher water consumers, but block rate pricing imposes an increasing marginal price to the consumer for increasing water consumption, which is found to be more efficient on residential water conservation (Olmstead et al. 2007). Comparing the demand elasticities of other cities under block rate water pricing, Oklahoma City can help to understand the effect of pricing on the price elasticity of water demand. In fact, Oklahoma City adopted a block rate pricing scheme in September 2014, with a higher second tier that would be implemented by 2016 to affect the most wasteful households using over 10,000 gallons per month (Gotcher, 2014). In addition, inclusion of more currently unknown demographic variables like household size (number of family members in household), the average age, and the education level of household members would improve water demand estimates and help target individual behavior for policy implementation. Unfortunately, more detailed household level data necessitates costly survey methods. This paper is able to provide basic intuition with data readily available to utilities and their regulators.

References

Arbués, F., M. García-Valiñas, and R. Martínez-Espiñeira. "Estimation of Residential Water Demand: A State-of-the-Art Review." *Journal of Socio- Economics.*, 32,1 (2003): 81-102.

Billings, R. B. "Specification of Block Rate Price Variables in Demand Models." *Land Economics* 58,3(1982): 386-94.

Billings, R. B. "Alternative Demand Model Estimators for Block Rate Pricing." *Journal of American Water Resources Association* 23,2(1987): 341-45.

Brock, F. V., K. C. Crawford, R. L. Elliott, G. W. Cuperus, S. J. Stadler, H. L. Johnson, and M. D. Eilts. "The Oklahoma Mesonet: A Technical Overview." *Journal of Atmospheric and Oceanic Technology* 12,1(1995):5-19.

Brookshire, D. S., H. S. Burness, J. M. Chermak, and K. Krause, "Western Urban Water Demand." *Natural Resources Journal* 42 (2002):873-98.

Bureau of Labor Statistics, (2015). http://www.bls.gov/regions/southeast/news-release/ConsumerPriceIndex_South.htm verified on January 30, 2015.

Cavanagh, S., M. Hanemann, and R. Stavins. "Muffled Price Signals: Household Water Demand Under Increasing-Block Prices." (2002). FEEM Working Paper. John F. Kennedy School of Government, Harvard University, Cambridge.

Census (2010). Available at http://www.census.gov/ verified on April 03, 2013.

Chicoine, D. L., and G. Ramamurthy. "Evidence on the Specification of Price in the Study of Domestic Water Demand." *Land Economics* 62,1 (1986):26-32.

City of Oklahoma City (2013a). Available at http://www.okc.gov/water/service/forms/householdwaterusage.aspx, verified on Feb. 20, 2013.

City of Oklahoma City. (2013b). Available at http://www.okc.gov/water/service/Forms/Rates_Fees.aspx verified on April. 5, 2013.

Cole, D. V. M., and E. Leslie. “Critic's Choice Essay: Some Thoughts on Oklahoma Plants and Summer 2011's Exceptional Drought.” *Oklahoma Native Plant Record* 11,1 (2011):75-76.

Dandy, G., T. Nguyen, and C. Davies. “Estimating Residential Water Demand in the Presence of Free Allowances.” *Land Economics* 73 (1997):125-39.

Espey, M., J. Espey, and W. D. Shaw. “Price Elasticity of Residential Demand for Water: A Meta-Analysis.” *Water Resouces Research* 33,6 (1997):1369-74.

Foster, H. S., and B. R. Beattie. “Urban Residential Demand for Water in the United States.” *Land Economics* 55,1 (1979):43-58.

Gaudin, S., R. C. Griffin, and R. C. Sickles.“Demand Specification for Municipal Water Management: Evaluation of the Stone-Geary Form.” *Land Economics* 77,3 (2001): 399-422.

Gotcher, M. “Personal Communication” Water Conservation Director, Oklahoma City Utilities. September 9, 2014.

Hewitt, J. A., and W. M. Hanemann. “A Discrete/Continuous Choice Approach to Residential Water Demand Under Block Rate Pricing.” *Land Economics* 71,2 (1995):173-92.

Hoffmann, M., A. Worthington, and H. Higgs, “Urban Water Demand With Fixed Volumetric Charging in a Large Municipality: The Case of Brisbane, Australia.” *Australian Journal of Agricultural Resource Economics* 50,3 (2006):347-59.

Jones, C. V., and J. R. Morris. “Instrumental Price Estimates and Residential Water Demand.” *Water Resources Research* 20,2(1984):197-202.

Kenney, D. S., C. Goemans, R. Klein, J. Lowrey, and K. Reidy. “Residential Water Demand Management: Lessons From Aurora, Colorado.” *Journal of American WaterResources Association* 44,1(2008):192-207.

Kjelgren, R., and F. Farag.“Quantifying Potential Urban Landscape Water Conservation Through Billing Data Analysis in Layton, Utah.” In: Proceedings, American Water Works Association (2002). Sources: Reuse, Resources, Conservation, Las Vegas, NV.

Lyman, R. A. “Peak and Off-Peak Residential Water Demand.” *Water Resources Research* 28,9(1992): 2159-67.

Mayer, P. W., and W. B. DeOreo. “Residential End Uses of Water.” (1999). American Water Works Association, Denver, CO.

Mesonet, 2013. Available at https://www.mesonet.org/ verified on Janauary 20, 2013.

Michelsen, A. M., J. T. McGuckin, and D. Stumpf. “Nonprice Water Conservation Programs As a Demand Management Tool.” *Journal of Americn Water Resources Association* 35,3(1999): 593-602.

Moss, J. Q., J. E. Hasse, J. R.Vogel, T. A.Boyer, and D.L. Martin. “Simple Lawn Irrigation Measurement Training for Master Gardeners and Homeowners.” *The Journal of Extention* 51,3 (2013). 3RIB7.

Nataraj, S., and W. M. Hanemann. “Does Marginal Price Matter? A Regression Discontinuity Approach to Estimating Water Demand.” *Journal of Environmental Economics and Management* 61,2 (2011):198-212.

Nieswiadomy, M. L., and D. J. Molina.“Comparing Residential Water Demand Estimates Under Decreasing and Increasing Block Rates Using Household Data.” *Land Economics* 65,3(1989):280-289.

Oklahoma Mesonet. “Heat and Drought Dominate 2012 Oklahoma Weather Headlines.” (2013a). Available at http://www.mesonet.org/index.php/news/article/heat_and_drought_dominate_2012_oklahoma_weather_headlines, verified on May 05, 2013.

Oklahoma Mesonet, (2013b). Available at www.mesonet.org, verified on Feb. 20, 2013.

Olmstead, Sheila M., W. M. Hanemann, and R. N. Stavins. “Water Demand under Alternative Price Structures.” *Journal of Environmental Economics and Management* 54,2 (2007):181-198.

Renwick, M. E., and R. D. Green. “Do Residential Water Demand Side Management Policies Measure Up? An Analysis of Eight California Water Agencies.” *Journal of Environmental Economics and Management* 40,1 (2000): 37-55.

Rockaway, T., J. Rivard, and B. Kornstein. “North America Residential Water Usage Trends since 1992.” *Water Research Foundation.* (2010).

Rockström, J. “Resilience Building and Water Demand Management for Drought Mitigation.” *Physics and Cheistry Earth, Parts A/B/C* 28,20 (2003):869-877.

Schleich, J., and T. Hillenbrand. “Determinants of Residential Water Demand in Germany.” *Ecological Economics* 68,6 (2009):1756-1769.

Stevens, T. H., J. Miller, and C. Willis, "Effect of Price Structure on Residential Water Demand." *Journal of American Water Resources Association* 28 (1992): 681-685.

Syme, G. J., B. E. Nancarrow, and C. Seligman."The Evaluation of Information Campaigns to Promote Voluntary Household Water Conservation." *Evaluation Review* 24,6(2000):539-578.

U.S. Energy Information Administration, (2015). Available at http://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_r20_m.htm, verified on January 29, 2015.

Table 1.1. Oklahoma City water service and sewer charges by date.

Type	Charges	Date				
		10/1/2008	**10/1/2009**	**10/1/2010**	**10/1/2011**	**10/1/2012**
Water Service	Base Charge	$7.02	$7.37	$9.75	$10.14	$10.55
	Use Charge/ 1000 gallons (3.79 m^3)	$2.15	$2.26	$2.35	$2.45	$2.55
Sewer	Base Charge	$1.54	$1.62	$2.78	$2.89	$3.01
	Use Charge/ 1000 gallons (3.79 m^3)	$3.09	$3.24	$3.37	$3.5	$3.65

Source: City of Oklahoma City (2013)

Table 1.2. Variable definitions and summary statistics.

Variables	Definition	Units	Mean	Std. Dev
Water consumption	Household water consumption per billing period	1000 gallons ($3.79\ m^3$)	8.87	10.88
Residential value (Income)	Value of the individual household used as a proxy for household income	Dollars	108,608	109,599
Marginal prices	Annual marginal prices over the billing period	Dollars/1000 gallons ($3.79\ m^3$)	2.35	0.10
Average prices	Average prices per billing period	Dollars/1000 gallons ($3.79\ m^3$)	8.28	2.31
Year built	Indicator variable, 1 if the household was built after 1994	0-1	0.15	0.36
Parcel size	Size of the parcel of individual households	Acres (ha)	1,712 (693)	826 (334)
Maximum temperature	Average monthly maximum temperature per billing period	°F (°C)	73.51 (23.06)	17.11 (-8.27)
Total rainfall	Total monthly rainfall per billing period	Inches (mm)	2.81 (71.37)	2.34 (59.44)
Gas prices	Regional gas prices per billing period	Dollars	3.21	0.48
Consumer Price Index	Regional Consumer Price Index per billing period	Dollars	137.76	3.64

Table 1.3. Variable estimates and standard error (in brackets) for demand of water for all billing periods, pre- and during- drought periods, and high consumption and low consumption periods using average price, Oklahoma City (July 2009 through December 2012). Coefficients are statistically significant at the 0.01 level.

Variables	**All Billing Periods**	**Pre-drought**	**Drought**	**High Consumption Period**	**Low Consumption Period**
Intercept	-3.81(0.12)	-2.37(0.17)	-3.74(0.13)	-10.77(0.17)	-2.95(0.12)
Ln(Parcel Size)	0.31(0.03)	0.31(0.03)	0.31(0.03)	0.48(0.04)	0.31(0.03)
Ln(Income)	0.28(0.02)	0.21(0.02)	0.31(0.02)	0.55(0.03)	0.20(0.02)
Ln(Average Price)	-0.38(0.01)	-0.67(0.05)	-0.49(0.01)	1.58(0.02)	-0.10 (0.01)
Year Built	-0.11(0.01)	-0.10(0.02)	-0.10(0.02)	-0.12(0.03)	-0.10(0.02)
Rainfall	-0.01(0.01)	-0.01(0.01)	0.01(0.01)	-0.01(0.03)	0.01(0.01)
Maximum temperature	0.01(0.01)	0.02(0.01)	0.01(0.01)	0.01(0.01)	0.01(0.01)
Number of observations	420,000	140,000	280,000	150,000	270,000
Number of households	10,000	10,000	10,000	10,000	10,000
Adjusted-R-Square	0.15	0.16	0.17	0.08	0.04

Note: Dependent variable is Ln (water consumption).

Table 1.4. Variable estimates and standard error (in brackets) for demand of water for all billing periods, high consumption period, and low consumption period using marginal price, Oklahoma City (July 2009 through December 2012). Coefficients are statistically significant at the 0.01 level.

Variables	**All Billing Periods**	**High Consumption Period**	**Low Consumption Period**
Intercept	-4.99(0.12)	-8.06(0.15)	-3.18(0.12)
Ln(Parcel Size)	0.36(0.03)	0.40(0.04)	0.32(0.03)
Ln(Income)	0.30(0.02)	0.48(0.03)	0.20 (0.02)
Ln(Marginal Price)	-0.66(0.02)*	1.49(0.03)	-0.01(0.03)
Year Built	-0.12(0.02)	-0.11(0.02)	-0.11(0.02)
Rainfall	-0.01(0.01)	-0.01(0.01)	0.01(0.01)
Maximum temperature	0.01(0.01)	0.01(0.01)	0.01(0.01)
Number of observations	420,000	150,000	270,000
Number of households	10,000	10,000	10,000
Adjusted-R-Square	0.15	0.06	0.03

* Statistically significant at the 0.1 level. Note: Dependent variable is Ln (water consumption).

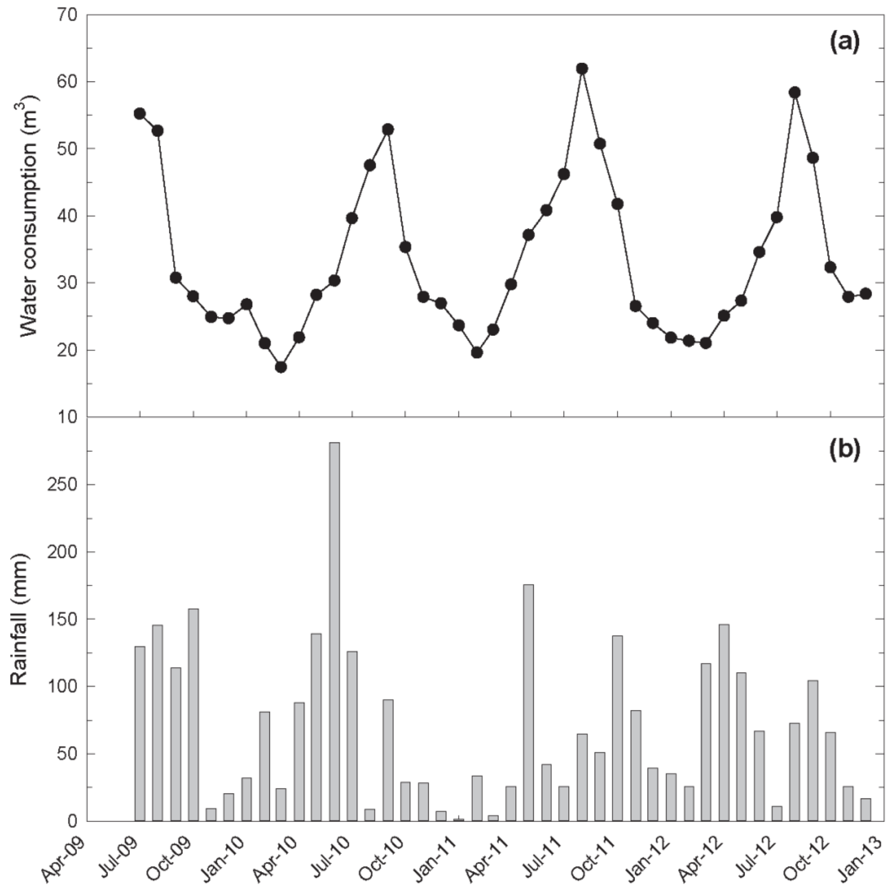

Figure. 1.1 Graphs showing (a) monthly average water consumption and (b) total monthly rainfall, July 2009 through December 2012 (Sources: City of Oklahoma City, 2013 and Mesonet, 2013).

CHAPTER II

HETEROGENEITY IN PREFERENCES FOR TURFGRASS ATTRIBUTES

ABSTRACT

Maintaining a desirable lawn entails choosing a turfgrass that can balance challenges associated with water requirements, salinity, shade, winter stress, and high maintenance cost. Turf producers and breeders attempt to produce new and improved turf cultivars, but they are largely unaware of the consumers' preferences for specific turfgrass attributes. This study determines consumers' preferences and willingness to pay for turfgrass attributes. The results of a survey of 1,179 household consumers indicate that preferences for stress tolerance turfgrass are highly heterogeneous. The preferred model specification (a latent class model) shows that household turf consumers are clustered in two broad classes; "*willing household consumer*" and "*reluctant household consumer*". Willing household consumers are characterized by high income and hobbyist, while reluctant household consumers are characterized by people of age more than 45 years. Results also indicate that willing household consumers are most likely to pay more for improved turfgrass attribute than reluctant household consumers.

For example, willing household consumers are willing to pay \$0.90 per square foot (ft^2), while reluctant household consumers are willing to pay \$0.77 per ft^2 more for low water requiring turf, (20,000 gallons per month) compared to high water requiring turf (60,000 gallons per month). This categorization of consumers may help sod producers and breeders in targeting willing household consumers and strategize how to reach the unwilling consumers.

Introduction

The turfgrass industry is expanding rapidly as one of the fastest growing segment of agriculture in the United States (U.S.) due to its visual benefits for growing residential and commercial properties (Morris, 2003; Haydu, Hodges, and Hall, 2006). Even though turfgrass does not provide food, fiber or animal feed, lives of millions of people are impacted by turfgrass in many different ways including their physical and mental health, and social well-being (Beard and Green, 1994). It is the major vegetative ground cover and is the most widely used ornamental plant in the U.S. (Emmons, 2000). Turfgrass occupies about 50 million acres (20.2 million ha) and it produces 40-60 billion annual revenue in the U.S. (Haydu, Hodges, and Hall, 2006; Morris, 2003). Approximately 75% of the total U.S. turfgrass coverage is home lawn acreage (Hull, Alm, and Jackson, 1994). The turfgrass industry provides economic benefit to diverse groups such as athletic field managers and superintendents, lawn care operators, architects, landscape designers, owners, contractors, and seed and sod producers. 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., 1993).

There is three times more acreage in lawns than there is acreage in irrigated corn, making turfgrass the largest irrigated crop of the U.S. in terms of surface area (Earth Observatory, 2005). According to the U.S. Geological Survey (USGS), of the 26 billion gallons (98 million m^3) of water consumed daily in the U.S., approximately 7.8 billion gallons (29.5 million m^3, 30%) are devoted to outdoor uses, mainly landscaping (Solley et al., 1998; Vickers, 2001). About 40-75% of household water use is accounted by turfgrass irrigation in arid and semi-arid regions (Morris, 2003; Mayer et al., 1999; Ferguson, 1987).

Due to climate change and more prolonged droughts and increasing public demands on water resources for human consumption, less potable water will be available in the future for lawn irrigation. As a result, mandatory irrigation restrictions, water audits, water bans, increases in potable water prices, and limits on turfgrass irrigation have already been imposed in many cities to reduce water scarcity during droughts and meet water demand for the long term (EPA, 2002; Kenny et al., 2009). In fact, governing bodies (water management districts, counties, and cities) are establishing restrictive irrigation guidelines and/or implementing ordinances that limit the use of certain turfgrass species or the turf acreage in urbans. Other problems such as salinity, shade, winter stress, and high maintenance also affect the proper turfgrass management. The lack of freshwater or municipally treated water has compelled the use of effluent or other low quality water such as rainwater or the reclaimed water for lawn irrigation purposes, and/or to target alternative plant materials in the lawn. Hot and dry climates (drought conditions) coupled with the use of low quality water may lead to higher concentrations of salt in the soil profile which adversely impact the growth of turfgrass and requires high maintenance. In addition, intrusion of seawater in the coastal cities and also the use of salt for road thawing have increased the salinity problem in turfgrass (Murdoch, 1987). Furthermore, several home lawns have a significant amount of shaded area and many turfgrass cultivars have largely been impacted by shade (Harivandi and Gibeault, 1996). Turfgrass loss during winter due to freezing temperature, termed as winter kill, is also one of the stress related problems of lawns (Frank, 2013). All these problems lead to increased demand of environmental stress tolerant (drought, salinity, shade, and winterkill) and water conserving turfgrass cultivars to cope with the stresses and to maintain the environmental benefits of turfgrass. Thus, efficient and sustainable turfgrass cultivars that are tolerant to the environmental stresses and require less water with wider geographical adaptation and broader regional impacts need to be developed. These improved turfgrass cultivars will help conserve potable water resources and human efforts, and increase the sustainability of the turfgrass industry.

When spending on lawn and landscaping, consumers are concerned with multiple attributes including attractiveness, ease of maintenance, cost, and stress tolerance. Sod producers and breeders often grow and develop a specific turf cultivar, but it may not reach consumers. Breeders may fail to convince producers of the salability of new and improved cultivars and consumers may be ignorant of the long term benefits of new cultivars. In order to meet demand, research scientists, producers, and turf industry practitioners must match turfgrass characteristics to buyer expectations and ability to pay. Unfortunately, there is a lack of information on consumer demand for turfgrass characteristics, something this research seeks to remedy. The objectives of this study are to determine household consumers' WTP for abiotic stress tolerant (drought, shade, winterkill, and salinity) and low maintenance attributes of turfgrass over southeastern and mid-southern states of the U.S., and address the possible causes of heterogeneity in the preference for the turfgrass attributes.

Some previous studies have shown that people are willing to pay for environmentally amenable goods and services (Engel and Potschke, 1998; Hu, Woods, and Bastin, 2009; Straughan and Roberts, 1999). However, concerns for the environment vary widely among the consumers especially in adoption of new products and services. Thus, it is necessary to conduct consumer research to understand consumers' attitude toward new products, i.e., improved turfgrass cultivars in this case. Little formal applied economic research has been performed on the consumers' preferences and willingness to pay (WTP) for specific turfgrass cultivars. Yue, Hugie, and Watkins (2012) used a choice experiment with real turf products to assess consumers' willingness to pay for low input and aesthetic attributes of turfgrass. They reported that consumers' preference and WTP are high for aesthetic and low maintenance attributes of turfgrass. Yue, Hugie, and Watkins (2012) limited their study to a small portion (N=128) of household consumers of turfgrass in Minnesota, USA. Consumer preferences for any good or service including turfgrass may be characterized by heterogeneity which is accounted by variation in location, weather, household and demographic characteristics, and other factors. Many choice experiments have shown that demographic characteristics such as age, education, and homeownership affect the willingness to pay for consumer goods (Birol et.al, 2006; Mahasuweerachi et.al, 2010). We expect preferences and behavior to vary by hard size and consumer attitudes, such as whether they view yard work as a hobby, or a necessary chore to save on professional landscape maintenance (Boyer et al, 2015; Ghimire et. al, forthcoming). Limiting the study to a particular area might not address the heterogeneity issue and may induce a biased demand forecasting model. This study covers five states (Florida, Georgia, Oklahoma, North Carolina, and Texas), the principal southern warm season turfgrass market, to study heterogeneity among consumers and also includes more stress related issues of turfgrass such as shade, salinity, and winter kill. The information on the consumers' preferences and WTP for these turfgrass attributes will contribute to connect the breeders' research, sod producers, and end retail consumer market. Yue, Hugie, and Watkins (2012) used mixed logit model (MLM) to allow for preference heterogeneity among household consumers to determine WTP for different turfgrass attributes. Along with the conditional logit model (CLM) and the MLM, the mixed logit model with interaction terms and the latent class model (LCM) are estimated in this study to access heterogeneity in the consumers' preferences and WTP for turfgrass attributes.

Methodology

Choice Experiment

The initial step to design the discrete choice experiment (DCE) was to select the goods to be valued in terms of attributes (stress tolerant turfgrass cultivars in this study). The attributes for the DCE were identified initially based on the literature review and with the consultation with turf breeders, physiologists, and other experts in turf industry. The selected attributes and their levels are reported in Table 2.1. The attributes were selected to study the economic paybacks of the stress tolerant turfgrass attributes. A $4^1 \times 3^3 \times 2^2 = 432$ number of unique lawn scenarios could be constructed from all the attributes and levels provided in Table 2.1. A fractional factorial design was constructed similar to Louviere, Hensher, and Swait (2000) where the numbers of profiles were selected to maximize D-efficiency, and each set had similar probability of choosing either of the alternatives. The fractional design (D-efficiency=96.4%) consisted of 18 sets of different lawn scenarios to evaluate. The set of 18 scenarios were randomly grouped in three different versions with six different DCE choice sets in each version.

Each choice set contained three lawn scenarios: A, B, and C where A and B composed of different turfgrass attributes differing in levels, and C was an option to select neither scenario which is an "opt out" option, also considered as a *status quo* or baseline alternative. Respondents were asked to choose one option among the three provided options assuming to be in the hypothetical situation if they had to buy one of the scenarios. An example of the DCE choice set is provided in Figure 2.1.

Data Collection

The online survey was conducted in November 2013 in collaboration with International Survey Sampling using Qualtrics as the internet interface. The survey was conducted with homeowners in five U.S. states (Florida, Georgia, Oklahoma, North Carolina, and Texas). The survey was composed of choice experiments, and questions about the households, attitudes, and demographics of the households. A total of 1,179 completed surveys were received. The descriptive statistics of the respondents are provided in Table 2.2. The respondents are mostly homeowners (98%) and they live in houses rather than apartments, condominiums, or mobile homes. The majorities of respondents have resided in their homes for more than 6 years (85%) and have yard size larger than 0.26 acres (68%). On average, respondents are 51 years of age with a deviation of approximately 15 years and about 64% of them are older than 45 years. Approximately 63% of the respondents have undergraduate or higher degrees. Respondents reported that they are 85% white and 47% females. The average income of the household is $67,455 with a deviation of $48,033. Approximately 55% of households have annual income $50,000 or higher.

In addition to the demographic and general household questions, attitudinal questions were also asked in the survey. Those attitudinal questions include rating their lawns, main attitude for lawn care (if lawn care is hobby or respondents want to save money to hire the lawn care service or both or any other reasons of lawn care), and their preferences for a United States Department of Agriculture (USDA) certified lawn or pesticide free lawn. The respondents were asked to rate their lawns as well as their neighbors' lawns on scale of 1 to 10 (where 1 is the worst and 10 is the best). On average, they provide higher rating to their lawns (7 out of 10 scale) than to their neighbor's lawns (6 out of 10 scale), indicating the belief of respondents that they take care of lawns better than their neighbors do. Of the respondents, 32% take care of their lawns as hobby, 29% take care of their lawns to save money by hiring the lawn care service, while 26% take care of their lawns for both purposes. Approximately 13% of the respondents gave other answers such as they were willing to do lawn care, but they are too old or lawn care is done by my husband or kids. The respondents in the survey are highly positive about the environmentally friendly product such as USDA certified (73%) and pesticide free turfgrass (82%).

Econometric Model

Conditional Logit Model. The DCE method in theory is based on the Lancaster's model of consumer choice (Lancaster, 1966), and theoretically and econometrically based on random utility theory (McFadden, 1974). The respondents are assumed to have random utility functional form which comprises the stochastic and deterministic components that can be represented as follows:

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs} \tag{1}$$

where V_{ij} is the deterministic component which we can observe for individual *i* for alternative *j* and choice set *s*, and ε_{ij} is the stochastic component. The observed utility is derived from the turf purchase scenario which depends on turfgrass attributes and levels in a particular scenario and can be represented as follows:

$$V_{ijs} = \boldsymbol{X_{ijs}\beta} \tag{2}$$

where $\boldsymbol{X_{ij}}$ is the vector of turfgrass attributes and *V* can be expressed as a grouping of turfgrass attributes as follows:

$$\begin{aligned} V_{ijs} = {} & No\ Change_{ijs} + \beta_1(WinterKill\ Low_{ijs}) + \beta_2(Winterkill\ Med_{ijs}) \\ & + \beta_3(Shade\ Tolerant_{ijs}) + \beta_4(WaterRequirement\ Low_{ijs}) \\ & + \beta_5(WaterRequirement\ Med_{ijs}) + \beta_6(Saline\ Tolerant_{ijs}) \\ & + \beta_7(Maintainencecost\ Low_{ijs}) + \beta_8(Maintenancecost\ High_{ijs}) \\ & + \beta_9(Average\ Price_{ijs}) \end{aligned} \tag{3}$$

where $\beta\,'$s are the parameters to be estimated for each attribute.

$WinterKill\ Low$ = 1 if no turf is damaged by winterkill with probability of 50%, 0 otherwise

$Winterkill\ Med$= 1 if 20% lawn is damaged by winterkill with probability of 50%, 0 otherwise

$Shade\ Tolerant$ = 1 if turf is tolerant to shade, 0 otherwise

$WaterRequirement\ Low =$ 1 if water requirement for the lawn is 20,000 gallons/month, 0 otherwise.

$WaterRequirement\ Med$ = 1 if water requirement for the lawn is 40,000 gallons/month, 0 otherwise.

$Saline\ Tolerant$ = 1 if turf is tolerant to salinity 0, otherwise.

$Maintainencecost\ Low =$1 if average maintenance cost is 20% less than now, 0 otherwise.

$Maintenancecost\ High =$1 if average maintenance cost is 20% more than now, 0 otherwise.

$Average\ Price$ = Average purchase price of turfgrass ($/ft^2) for a 5000 square feet lawn.

No change is alternative specific constant which captures the effect (difference) in the utility of a respondent's selection of option C in a choice set compared to Option A and B. The *No change* is specified to be equal to 1 when option C is selected and 0 if option A or B is selected.

Consumers will choose a particular option *j* if it's utility is higher than those for other alternatives. Assuming that the relationship between utility and attributes is linear in the parameters and variables function, the error terms ε_{ij} are independent and identically distributed (IID) and follow a type I extreme value distribution, the probability of alternative *j* being chosen can be expressed as:

(4) $$p_{ijs} = \frac{e^{(\boldsymbol{X}_{ijs}\boldsymbol{\beta})}}{\sum_{k=1}^{J} e^{(\boldsymbol{X}_{isk}\boldsymbol{\beta})}}$$

The log likelihood function for the choices made by all individuals is determined as:

(5) $$\ln l = \sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{s=1}^{S} d_{ijs}(\ln(p_{ijs}))$$

where d_{ijs} is a binary variable that takes the value of 1 if a person *i* choose alternative *j* for the choice set *s,* 0 otherwise.

Mixed Logit Model. There has been wide use of the CLM to estimate consumers' utility in the choice experiment literature. The CLM assumes same parameters for all consumers for the attributes which indicates that all consumers have same preference for the attributes in question (Lusk and Parker, 2009; Peterson and Yosida, 2004). However, heterogeneity in preferences may exist due to differences in location, demographics, and attitudes. Among several methodologies the MLM is one of the methods that account for respondents' preference heterogeneity which enables the estimation of unbiased estimates with accuracy and reliable demand for welfare measurements (Greene, 1997). Allowing model parameters to vary randomly over individuals, the MLM is characterized by accommodating heterogeneity as a continuous function of parameters (Train, 1998; Mcfadden and Train, 2000). The MLM incorporates unobservable heterogeneity by modelling a distribution of β_i.

(6) $$\boldsymbol{\beta}_{\boldsymbol{ik}} = \boldsymbol{\beta}_k + \boldsymbol{\sigma}_k \eta_{ik}$$

The (relative) utility associated with each individual i for attribute *k* is represented in a discrete choice model by a utility expression of the general form in equation (6) where η_{ik} is an error term with distribution f (η_{ik}). Hence, $\boldsymbol{\beta}_{\boldsymbol{ik}}$ is a random variable with distribution f($\boldsymbol{\beta_{ik}}$), mean $\boldsymbol{\beta_k}$ and standard deviation $\boldsymbol{\sigma}_k$. For a given value of η_i the conditional probability of choice *j* will be:

(7)
$$p_{ijs} = \frac{\exp(\boldsymbol{X_{js}}(\overline{\boldsymbol{\beta}} + \boldsymbol{\sigma}\eta_i)}{\sum_{k=1}^{J} \exp(\boldsymbol{X_{sk}}(\overline{\boldsymbol{\beta}} + \boldsymbol{\sigma}\eta_i)}$$

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 simulated log likelihood function. In the MLM, the observable attributes *V* can be expressed as a grouping of turfgrass attributes as in equation (1) with each β 's having a distribution as in equation (6). The maximum simulated log likelihood function for the choices made for *R* number of random draws is determined as:

(8)
$$\ln l = \sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{s=1}^{S} d_{ijs}(\ln \frac{1}{R}\sum_{r=1}^{R} p_{ijsr})$$

Since basic MLM cannot identify the sources of preference heterogeneity among the consumer, the MLM with interaction terms was estimated to test the difference in preference for different groups of income level, age, gender, race, education, states, yard size, and lawn care attitudes. The interaction model can be specified as follows:

(9)
$$\begin{aligned} V_{ijs} = \boldsymbol{X_{ijs}\beta_i} + \ \delta(\boldsymbol{X_{ijs}} \times \boldsymbol{Age}) + \ \gamma(\boldsymbol{X_{ijs}} \times Female) + \vartheta(\boldsymbol{X_{ijs}} \times Race) \\ + \rho(\boldsymbol{X_{ijs}} \times \boldsymbol{State}) + \mu(\boldsymbol{X_{ijs}} \times \boldsymbol{Income}) + \theta(\boldsymbol{X_{ijs}} \times \boldsymbol{Lawncare}) \\ + \omega(\boldsymbol{X_{ijs}} \times \boldsymbol{Yard\ size}) + \tau(\boldsymbol{X_{ijs}} \times \boldsymbol{Education}) \end{aligned}$$

where *X* is a vector of variables specified as in equation (3); $\boldsymbol{Age}$ is the vector of age which is separated in three dummy variables that are coded 1 if the individual is in that age-group and 0 otherwise; *Female* is a dummy variable if individual is female and 0 otherwise; *Race* is a dummy variable if individual is Caucasian and 0 otherwise; ***State*** is a vector of state (i.e. Florida, Georgia, Oklahoma, North Carolina, Texas) and is coded 1 if the individual lies in that state and 0 otherwise; ***Income*** is a vector of income that is separated in five categories and is coded 1 if the individual lies in that income category and 0 otherwise; $\boldsymbol{Lawncare}$ is the vector of lawn care attitude which is separated in four dummy variable categories and coded 1 if individual possesses that attitude of lawn care and 0 otherwise; ***Yard size*** is a vector of size of yard of respondents that is separated in three categories and is coded 1 if the individual lies in that yard size category and 0 otherwise; ***Education*** is a vector of levels of education that is separated in three categories and is coded 1 if the individual lies in that education category and 0 otherwise; and $\delta, \gamma, \vartheta, \rho, \theta, \omega, \tau,$ and μ are the parameters to be estimated for respective interaction variables.

Latent Class Model. The LCM in contrast to the MLM is a semi parametric version of the MLM where heterogeneity is derived from different discrete classes with each class having its own parameters (Bhat, 1997; Wedel and Kamakura, 2000). In the MLM, utility is determined as a continuous function, however, consumers' preferences may also cluster (Boxall and Adamowicz, 2002; Patunru, Braden, and Chattopadhyay, 2007). The sources of heterogeneity can be identified in the LCM as the characteristics of the covariates in the classes. The LCM can be regarded as a special case of the MLM with β_i taking a finite number of discrete class (C) with corresponding probabilities as:

(10)
$$\text{Probability of choosing option } j \mid \text{c} = \frac{e^{(\boldsymbol{X_{ijs}\beta_c})}}{\sum_{k=1}^{j} e^{(\boldsymbol{X_{isk}\beta_c})}}$$

The probabilities of each class are estimated using conditional logit as follows:

(11) $$\text{Prob(class = c)} = Q_{ic} = \frac{\exp(\theta_c z_i)}{\sum_{c=1}^{C} \exp(\theta_c z_i)}$$

where z_i is a vector of class specific variables such as income, age, or attitudes that have effect on class probabilities and θ_c is the corresponding parameter vector for class c. The vector z_i can comprise only constant if case-specific variables are not available or do not explain the class probability. The maximum simulated likelihood method is applied as follows:

(12) $$\ln l = \sum_{i=1}^{N} \sum_{j=1}^{J} \sum_{s=1}^{S} \sum_{c=1}^{C} d_{ijsc} \ln(Q_{ic} * \text{Probability of choosing option } j \text{ |c)}$$

Measures of Fit. The best fitting model as well as best fitting class for the LCM is identified based on the balanced assessment of fitting parameters such as Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and Pseudo R^2. The information criteria are calculated as follows:

(13) $$AIC = -2(\ln L - P)$$

$$BIC = -\ln L + (\frac{M ln N}{2})$$

$$Pseudo\ R^2 = 1 - \frac{\ln L(Model)}{\ln L\ (Null)}$$

where $\ln L$ the log likelihood value at convergence, P is number of parameters, and N is number of sample size. Equation (13) indicates that increase in N and P penalizes AIC and BIC. The best fitting model maximizes $Pseudo\ R^2$, closer to 1.

Willingness to Pay. The welfare measure in the DCE is done by estimating WTP for the particular attribute using the following formula:

(14) $$WTP = -1\left(\frac{\beta_k}{\beta_{price}}\right)$$

where *WTP* is the welfare measure of attribute *k*, β_k are the marginal utility of the k^{th} attributes of turfgrass included in the analysis, and β_{price} is the marginal utility of increase in purchase price of turfgrass. This formula represents the marginal rate of substitution between average purchase price and attribute in question.

Results and Discussions

All models are specified so that the probability of selecting a particular turfgrass attributes scenario is a function of attributes of that scenario and of the option C (*No Change*) using the 7,026 choices elicited from 1,179 respondents.

Conditional Logit Model

The first model estimated is the CLM (Table 2.3). The coefficient estimates for the turfgrass attributes show the expected signs and most of the variables are significant at 1% level except the saline tolerance attribute. The *No Change* is significantly positive which indicated that respondents on average are reluctant to choose options (A and B) provided in the survey. The negative sign price coefficient indicates that the homeowners' utility decreases as the purchase price of turfgrass increases. Low and medium lawn area lost due to winterkill was preferred over larger lawn area lost due to winterkill. The positive sign on shade tolerance and saline tolerance coefficients indicates that homeowners prefer shade tolerant turf and saline tolerant turf. The regression results also indicate that household turfgrass consumers prefer low and medium water requirements rather than high water requirements for watering their lawns. The positive sign on the low maintenance cost attribute shows that homeowners prefer low maintenance turf rather than no change. The negative sign in high maintenance cost indicates that homeowners prefer no change rather than high maintenance cost for turfgrass.

Mixed Logit Model

All attributes except the price attribute are specified randomly and normally distributed (Train, 1998; Revelt and Train, 1998; Morey and Rossmann, 2003; Carlsson et al., 2003) since the normal distribution is a good approximation and gives a better fit than any other distribution with no difficulty in interpretation and estimation (Meijer and Rouwendal, 2006; Sillano and de Dios Ortand, 2005). The MLM estimates reveal significant and large derived standard deviations for most of the variables suggesting heterogeneity in preferences (Table 2.3). To determine the source of heterogeneity, the parameters are interacted with different categories of the demographic and attitudinal characteristics of the respondent such as yard size, age, gender, race, education, income, and attitude for lawn care (Table 2.3). The results show the expected signs for all the parameters and only the significant interaction variables are reported in Table 2.3. A positive and significant utility estimate indicates that the utility of choosing an option increases with the attribute in question or its interaction with the demographic variables. In general, the variables higher yard size, higher income, white, female, and being hobbyist increase the utility of the household consumer, causing him or her to choose the improved turfgrass attributes (such as low and medium levels of stress in turfgrass compared to high). However, respondents over 45 years of age compared to younger respondents (<30 years) are averse to choose the improved turfgrass attributes options in the choice set. The fit statistics shows that the MLM and the MLM with interaction are statistically different and superior to the CLM in terms of overall fit and welfare estimate, consistent with the findings of previous studies (Breffle and Morey, 2000; Layton and Brown, 2000; Carlsson, Frykblom, Liljenstolpe, 2003; Kontoleon, 2003; Lusk, Morey and Rossmann, 2003).

Latent Class Model

The LCM is used to determine the different classes of consumers with homogeneous preference nature within each class. Determining the optimal classes requires the balanced assessment of the fitting statistics (Andrews & Currim, 2003; Louviere, Hensher, and Swait, 2000; Wedel & Kamakura, 2000). The best fitting class has the smallest AIC, BIC parameters, and highest Pseudo R^2. The parameters are estimated for five classes (Table 2.6). As the number of classes increases AIC and BIC parameters continue to decrease and Pseudo R^2 continues to increase (Table 2.6). Most of the variables are highly significant and more reliable in the two class model than the three class and higher number class models. Class three, four, and five have a probability of their class breakdown being a reliable prediction of less than 10%. Thus considering class probability more than 10% for each class and the decrease in the AIC,BIC, and that the increase in Pseudo R^2 is not very high going from class 2 to 3, 3 to 4, and 4 to 5, a two class model is chosen as the best fitting model. Inclusion of demographic and attitudinal characteristics (age, income, lawn care attitude) as covariate provides a better fit to the model. Thus, the two class LCM with covariates is chosen as the best fitting model.

The result of the two class LCM is provided in Table 2.4 which comprises of two sections; the top section gives the utility coefficient of each attributes of the turfgrass for two classes while the bottom section gives the coefficients of class membership for demographic and attitudinal variables which are used as covariates in the LCM. The membership coefficients of the variables for second class are normalized to zero to allow the identification of remaining coefficients of the model (Boxall and Adamowicz, 2002). The utility coefficients for the turfgrass attributes show the expected signs for both classes except for saline tolerant attribute in the second class.

The two classes are categorized as the "*willing household consumer*" and "*reluctant household consumers*" based on the values of *No Change* variable. For Class 1, the *No Change* was significantly negative which indicates that the respondents belonging to this class are very positive towards new changes in their lawn. This also indicates that they are more open to adopting the stress-tolerant turfgrass cultivars. While for class 2, the *No Change* was positive and significant, suggesting that they are reluctant to adopt new and improved turfgrass attributes.

Class Characterization and Covariates. The bottom section of Table 2.4 gives the class membership in the LCM of the respondents based on their demographic and attitudinal characteristics. A significantly positive variable indicates that the variable increases the probability of a respondent to be in that particular class, while significantly negative variable indicates that the variable decreases the respondents probability to be in that class. The class membership functions indicates that the persons who take care and maintain their lawn as a hobby are significantly likely to be a willing household consumers compared to other people (Table 2.4). Likewise, high income people are also significantly likely to be a willing household consumer and people of age more than 45 years are less likely to be a willing household consumers (i.e., reluctant household consumers).

Comparison of the Models

The MLM, the MLM with interaction, and the LCM provided better fit than the CLM which is consistent with the findings of previous studies (Abidoye et al., 2011; Chung, Han, and Boyer, 2009; Train, 2003; Chung et al., 2012). A likelihood ratio test rejects that the CLM, MLM, MLM with interaction, and LCM are same. Statistical difference among the four models reinforces the use of best fit model (Table 2.5). Among four models (CLM, MLM, MLM with interaction, and LCM), the best fit model is LCM (the lowest AIC and BIC, and highest Pseudo R^2).

Homeowner's Valuation for Turfgrass Attributes

Considering the best fitting model (LCM), the coefficient estimates from random utility model in Table 2.4 is utilized to determine the marginal WTP/WTA. Table 2.6 reports the marginal WTP/WTA values for each turfgrass attribute which was estimated as in equation (14) for each classes of the LCM. The marginal value of each attribute represents the consumers' compensation to adopt an attribute (WTP) or to forego an attribute (WTA). Household turfgrass consumers are willing to pay more for low vs. high compared to medium vs. high (for winterkill and water requirement attributes). They are also willing to pay for saline tolerant turfgrass (with exception of "Reluctant Household Consumer" class of the LCM) and shade tolerant turfgrass. Household turfgrass consumers are willing to pay more for lower maintenance cost compared to no change while they are willing to accept the compensation if the maintenance cost is higher from current situation.

The willing household consumers are generally willing to pay more than reluctant household consumers for most of the attributes included in this study. For example, willing household consumers are willing to pay \$0.35 per square foot (ft^2) while reluctant household consumers are willing to pay \$0.28 per ft^2 for shade tolerant turfgrass; willing household consumers are willing to pay \$0.90 per ft^2 while reluctant household consumers are willing to pay \$0.77 per ft^2, more for low water requiring turf (20,000 gallons per month) compared to high water requiring turf (60,000 gallons per month); willing household consumers are willing to pay \$0.46 per ft^2 while reluctant household consumers are willing to pay \$0.42 per ft^2 more for medium water requiring turf (40,000 gallons per month) compared to high water requiring turf (60,000 gallons per month); willing household consumers are willing to pay \$0.08 per ft^2 while reluctant household consumers are willing to accept \$0.08 per ft^2 for saline tolerant turfgrass. However, for some attributes such as low winterkill vs. high winterkill and low maintenance cost vs. no change (Figure 2.2) the willingness to pay amounts for the willing household consumers are lower than the reluctant household consumers.

Summary and Conclusions

This study contributes to the study of preferences and willingness to pay for improved warm season turfgrass attributes in the southeastern and mid-southern U.S. This is the second study to evaluate the preferences and willingness to pay for the turfgrass attributes and first to incorporate preference heterogeneity and assess its sources in the preference for turfgrass attributes. In this study, the basic CLM, MLM, the MLM with interactions, and the LCM are estimated. The CLM does not incorporate heterogeneity, while other three models incorporate heterogeneity. Interacting demographic and attitudinal characteristics in the MLM with interactions and the LCM are estimated to evaluate the probable sources of preference heterogeneity for turfgrass attributes. Using a balanced assessment of fit statistics, the LCM with two classes of household consumers was the best fitting model. Two classes of LCM were identified with homogeneous preference approach within each class. Class 1 was characterized as "*willing household consumer"*, while class 2 was characterized as "*reluctant household consumer"*. Among two classes, willing household consumers are willing to pay more for the turfgrass attributes in general. The willing household consumers are most likely high income people, hobbyists, and younger than 45 years, a categorization which was also supported by the MLM with interactions model.

The results show that preferences for stress tolerant turgrass attributes are highly heterogeneous and the major sources of the heterogeneity could be demographics such as age, income, and attitudes. However, more research is required to identify the major causes of preference heterogeneity among the household turfgrass consumers. The results obtained in this study could be helpful for policy makers, sod producers, and breeders to target the potential adopters and strategize how to reach the reluctant consumers.

References

Abidoye, B.O., H. Bulut, J.D. Lawrence, B. Mennecke, and A.M. Townsend."U.S. Consumers' Valuation of Quality Attributes in Beef Products." *Journal of Agricultural and Applied Economics* 43, 1 (2011):1-12.

Andrews, R.L., and I.S. Currim. "A Comparison of Class Retention Criteria for Finite Mixture Logit Models." *Journal of Marketing Research*, *40*, 2 (2003):235-243.

Beard, J. B., and R. L. Green. "The Role of Turfgrasses in Environmental Protection and Their Benefits to Humans." *Journal of Environmental Quality*, *23*,3(1994): 452-460.

Bennett, J. and R. Blamey, eds. The Choice Modelling Approach to Environmental Valuation. 2001. Edward Elgar Publishing,

Bhat, C.R. "An Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel." *Transportation Science* 31,1 (1997): 34-48.

Birol, E, K. Karousakis, and P. Koundouri. "Using A Choice Experiment to Account for Preference Heterogeneity in Wetland Attributes: The Case Of Cheimaditida Wetland In Greece." *Ecological Economics* 60,1 (2006): 145-56.

Bormann, F. H., D. Balmori, and G.T. Geballe. "Redesigning the American Lawn: A Search for Environmental Harmony." 2001. Yale University Press.

Boyer, T., P. Kanza, M. Ghimire, and J. Moss. "Household Adoption of Water Conservation and Resilience Under Drought: The Case of Oklahoma City Water Economics and Policy." *Water Economics and Policy* 1, 2 (2014).

Boxall, P.C., and W.L. Adamowicz. ''Understanding Heterogeneous Preference in Random Utility Models: A Latent Class Approach.'' *Environmental and Resource Economics* 23(2002):421–46.

Breffle, W., E. Morey, Investigating Preference Heterogeneity in a Repeated Discrete-Choice Recreation Demand Model of Atlantic Salmon Fishing. Marine Resource Economics, 15(2000): 1-20.

Carlsson, F., P. Frykblom, C. Liljenstolpe. Valuing Wetland Attributes: An Application of Choice Experiments. *Ecological Economics*, 47 (2003): 95-103.

Chung, C., S. Han, and T. Boyer. ‘‘Valuing Quality Attributes and Country Equity in the Korean Beef Market.’’ *Journal of Agricultural Economics* 60, 3(2009):682–98.

Chung, C., B.C. Briggeman, and S. Han “Willingness-to-Pay for Beef Quality Attributes: A Latent Segmentation Analysis of Korean Grocery Shoppers.” *Journal of Agricultural and Applied Economics* 44.4 (2012): 447.

Earth Observatory. 2005. Available at http://earthobservatory.nasa.gov/Study/Lawn/lawn.html. verified on September 10, 2014.

Emmons, R. Turfgrass Science and Management. Delmar Pub. 3rd Ed. Hall, C.R. (Coordinator). Economic Impacts of the Green Industry in the United States. 2007. Southern Coop. Ser. Bull. 406-S-1021/S-290 Multistate Res Project. 81 p.

Engel, U. and M. Potschke. “Willingness to Pay for the Environment: Social Structure, Value Orientations and Environmental Behavior In A Multilevel Perspective.” *Innovation: The European Journal of Social Science Research* 11, 3(1998):315-32.

Environmental Protection Agency. Cases in Water Conservation: How Efficiency Programs Help Water Utilities Save Water and Avoid Costs. 2002. Washington, DC: US EPA.

Ferguson, B.K. “Water Conservation Methods in Urban Landscape Irrigation: An Exploratory Overview.” *Water Resources Bulletin* 23 (1987):147–152.

Frank W.K. Freeze Injury on Turf. 2013. Available at http://msuturf.blogspot.com/2013/05/freeze-injury-on-turf.html. verified on November 29, 2014.

Ghimire, M., T. Boyer, C. Chung, and J. Moss. “Estimation of Residential Water Demand under Uniform Volumetric Water Pricing.” *Journal of Water Resource Planning and Management.* Forthcoming 2015.

Greene, W. H., and D. A. Hensher. “A Latent Class Model for Discrete Choice Analysis: Contrasts with Mixed Logit.” *Transportation Research Part B: Methodological* 37,8 (2003), 681-698.

Greene, W.H. Econometric Analysis. 1997. Prentice Hall, New Jersey.

Harivandi, A. and V. A. Gibeault. 1996. Managing Lawns in Shade. Oakland: University of California Division of Agricultural and Natural Resource Publication 7214.

Haydu, J.J., A.W. Hodges, and C.R. Hall. “Economic Impacts of the Turfgrass and Lawncare Industry in the United States.” 2006. University of Florida, Coop. Ext. Serv., Gainesville, FL. EDIS Bull. FE632 Available at http://edis.ifas.ufl.edu/FE632.

http://www.utextension.utk.edu/hbin/scsbeconomic.htm verified on January 2, 2013.

Hu, W., T. Woods, and S. Bastin. “Consumer Acceptance and Willingness to Pay for Blueberry Products With Nonconventional Attributes.” *Journal of Agricultural and Applied Economics* 41, 1(2009):47-60.

Hull, R. J., S. R. Alm, and N. Jackson. “Toward Sustainable Lawn Turf.” *Handbook of Integrated Pest Management for Turf and Ornamentals* (1994).

Kenny, Joan F., L. B. Nancy, S. H. Susan, S. L. Kristin, K. L. John and A. M. Molly Estimated Use of Water in the United States in 2005. No. 1344. US Geological Survey, 2009.

Kjelgrcn, R., L. Ruppi, and D. Kilgren. “Water Conservation in Urban Landscapes.” 2000. *Atlanta* 297(563):1-26.

Kontoleon, A. Essays on Non-Market Valuation of Environmental Resources: Policy and Technical Explorations, Ph.D. Thesis. 2003. University College London, University of London.

Lancaster, Kelvin J. “A New Approach to Consumer Theory.” *The Journal of Political Economy* (1966): 132-157.

Layton D., G. Brown. “Heterogeneous Preferences Regarding Global Climate Change.” *Review of Economics and Statistics* 82 (2000): 616–24.

Louviere, J. J., A. H. David, and J.D. Swait. “Stated Choice Methods: Analysis and Applications.” 2000. Cambridge University Press.

Lusk J.L., J. Roosen, J.A. Fox. “Demand for Beef from Cattle Administered Growth Hormones or Fed Genetically Modified Corn: A Comparison of Consumers in France, Germany, the United Kingdom and the United States.” *American Journal of Agricultural Economics*, 85, 1 (2003):16-29.

Lusk, J., and N. Parker. ‘‘Consumer Preferences for Amount and Type of Fat in Ground Beef.’’ *Journal of Agricultural and Applied Economics* 41,1 (2009):75–90.

Mahasuweerachai, P., T. A. Boyer, D. M. Balsman, and D.E. Shoup. “Estimating Demand for Urban Fisheries Management: An Illustration of Conjoint Analysis as a

Tool for Fisheries Managers." *North American Journal of Fisheries Management* 30, 5 (2010): 1339-1351.

Mayer, P.W. , W.B. Deoreo, E.M. Opitz, J.C. Kiefer, W.Y. Davis, B. Dziegielewski, and J.O. Nelson. "Residential End Uses of Water." 1999. Denver, CO: American Water Works Association.

McFadden, D. "The Measurement of Urban Travel Demand." *Journal of Public Economics* 3,4 (1974): 303-28.

McFadden, D., and K. Train. "Mixed MNL Models for Discrete Response." *Journal of Applied Econometrics* 15,5 (2000): 447-70.

Meijer, E., and J. Rouwendal. "Measuring Welfare Effects in Models with Random Coefficients." *Journal of Applied Econometrics* 21, 2 (2006): 227-244.

Morey, E.R., K.G. Rossmann. "Using Stated-Preference Questions to Investigate Variations in Willingness to Pay for Preserving Marble Monuments: Classic Heterogeneity, Random Parameters, and Mixture Models." *Journal of Cultural Economics,* 27, 4 (2003.): 215-29.

Morris,K. "National Turfgrass Research Initiative." National Turfgrass Federation, Inc. , and National Turfgrass Evaluation Program, Beltsville. 2003.

Murdoch,C.L. "Water... The Limiting Factor for Golf Course Development in Hawaii." 1987. New York.

Patunru, A.A., J.B. Braden, and S. Chattopadhyay. ''Who Cares About Environmental Stigmas and Does it Matter? A Latent Segmentation Analysis of State Preferences for Real Estate.'' *American Journal of Agricultural Economics* 89, 3 (2007): 712–26.

Peterson, H. H., and K. Yoshida. “Perceptions of Quality and Willingness-to-Pay for Imported Rice in Japan.” *Journal of Agricultural and Applied Economics* 36(2004):123–142.

Revelt, D., K. Train, 1998. “Mixed Logit with Repeated Choices.” *Review of Economics and Statistics* 80, 4 (1998): 647-657.

Sillano, M. and J.D. Ortand, Willingness-To-Pay Estimation with Mixed Logit Models: Some New Evidence. *Environment and Planning* A 37, 3 (2005):525 - 550.

Solley, W. B., R. R. Pierce and H. A. Perlman. Estimated Use of Water in the United States in 1995 (USGS Circular 1200). 1998. USGS. Reston, VA. p.27. Statistics 80, 647-657.

Straughan, R.D. and J.A.Roberts. “Environmental Cassation Alternatives: A Look at Green Consumer Behavior in the New Millennium.” *Journal of Consumer Marketing* 16, 6 (1999.): 558-75.

Train, K. “Recreation Demand Models with Taste Variation.” *Land Economics* 74 (1998):230-239.

Train, K. Discrete Choice Methods with Simulation. 2003. Cambridge University Press,

U.S. Census Bureau. Annual Benchmark Report for Wholesale Trade: Current Business Reports (multiple reports and updates). 2007. U.S. Department of Commerce, Washington, DC.

Vickers, A. Handbook of Water Use and Conservation. 2001. Water Plow Press. Amherst, MA. p. 140.

Wedel, M., and W. Kamakura, Market Classification: Conceptual and Methodological Foundations. 2000. Boston: Kluwer Academic Publishers.

Yue, C., K. Hugie and E. Watkins. "Are Consumers Willing to Pay More for Low-Input Turfgrasses on Residential Lawns? Evidence from Choice Experiments." *Journal of Agricultural and Applied Economics* 44 (2012):549.

Table 2.1. Turfgrass attributes and levels

S.N.	Attributes	Attribute Levels
1	Lost lawn area to winter kill (50% probability)	Low (0%) Medium (20%) High (40%) - base
2	Shade tolerant	Yes No - base
6	Watering your lawn (gallons/year)	Low (20,000 gallons) Medium (40,000 gallons) High (60,000 gallons) - base
4	Sod tolerant to salinity	Yes No - base
5	Maintenance and reoccurring cost (mowing, spraying, grooming, fertilizing, and weeding)	Low (20% less than now) High (20% more than now) No Change - base
6	Total average purchase price for a lawn of 5000 square foot ($\$/ft^2$)	\$0.20, \$0.40, \$0.60, \$0.80

Table 2.2. Summary statistics of general, demographic, and attitudinal characteristics of the respondents.

Variables	Definition	Mean/ Percentage	Std. Dev.
General Characteristics			
Own	1 if house is owned, 0 otherwise	0.98	
Years house owned	Average years of house owned	20	14
House owned < 6 years	1 if house is owned < 6 years, 0 otherwise	0.15	
House owned 6-20 years	1 if house is owned for 6-20 years, 0 otherwise	0.54	
House owned >20 years	1 if house is owned for >20 years , 0 otherwise	0.30	
Yard Size (acres)	Average size of the yard	0.52	0.45
Yard size < 0.26 acres	1 if yard size is < 0.26 acres, 0 otherwise	0.31	
Yard size 0.26-0.40 acres	1 if yard size is 0.26-0.40 acres, 0 otherwise	0.31	
Yard size > 0.40acres	1 if yard size is > 0.40 acres, 0 otherwise	0.37	
Attitudinal Characteristics			
Rating of own lawn	Average rating of their own lawn	7	2
Rating of neighbor's Lawn	Average rating of their neighbor's lawn	6	2
Hobbyist	1 if lawn care is hobby , 0 otherwise	0.32	
Saver	1 if lawn care is done to save money for hiring services, 0 otherwise	0.29	
Both (hobbyist and saver)	1 if both, 0 otherwise	0.26	
Other	1 if other reason for lawn care, 0 otherwise	0.13	
Interested in USDA certified turf	1 if respondent is interested in USDA certified turf, 0 otherwise	0.73	
Interested in no pesticide turf	1 if respondent is interested to keep pesticide free lawn, 0 otherwise	0.82	

Table 2.2. Contd...

Variables	Definition	Mean/ Percentage	Std. Dev.
Demographic Characteristics			
Age (Years)	Average Age	51	15
Age <30	1 if age is <30, 0 otherwise	0.11	
Age 30-45	1 if age is 30-45, 0 otherwise	0.25	
Age >45	1 if age is >45, 0 otherwise	0.64	
Female	1 if respondent is female, otherwise	0.47	
White	1 if respondent is white, 0 otherwise	0.85	
Education <=high school	1 if respondent have high school or less education, 0 otherwise	0.38	
Education (Undergraduate)	1 if respondent has undergraduate, 0 otherwise	0.41	
Education(>Undergraduate)	1 if respondent have education more than undergraduate, 0 otherwise	0.22	
Income	Average Income	$67,455	$48,033
Income <$50,000	1 if income is less than $50,000, 0 otherwise	0.49	
Income $50,000-$74,999	1 if income is in between $50,000-$74,999, 0 otherwise	0.42	
Income $75,000-$100,000	1 if income is in between $75,000-$100,000, 0 otherwise	0.12	
Income>$100,000	1 if income is >$100,000, 0 otherwise	0.05	

Table 2.3. Parameter estimates of conditional logit, mixed logit and mixed logit with interaction model.

	Conditional logit	Mixed logit		Mixed logit with interaction	
Variables	**Estimates**	**Estimates**	**Std. Dev**	**Estimates**	**Std. Dev**
No Change	0.15(0.07)**	0.401(0.11)***	-0.08(1.23)	0.42(0.11)**	2.20(0.09)***
Lawn lost by winterkill (Low vs High)	0.50 (0.05)***	0.71(0.08)***	0.81(0.40)***	0.63(0.29)***	0.19(0.17)
Lawn lost by winterkill (Medium vs High)	0.25(0.05)***	0.25(0.07)***	1.06(0.30)***	0.23(0.29)	0.34(0.19)*
Shade Tolerant	0.44(0.03)***	0.59(0.07)***	-0.07(0.75)	0.22(0.33)	0.69(0.07)***
Water requirement (Low vs High)	1.09(0.05)***	1.40(0.01)***	-0.50(0.46)	1.25(0.30)***	0.89(0.08)***
Water requirement (Medium vs High)	0.56(0.05)***	0.72(0.09)***	-0.05(0.65)	0.68(0.28)***	0.12(0.14)
Saline Tolerant	0.04(0.04)	0.06(0.05)***	0.37(0.38)	0.41(0.22)**	0.51(0.09)***
Maintenance cost (Low vs No change)	0.16(0.05)***	0.20(0.07)***	0.01(0.58)***	0.003(0.28)	0.21(0.19)
Maintenance cost (High vs No change)	-0.35(0.04)***	-0.85(0.15)***	1.90(0.34)***	-0.32(0.29)	0.41(0.12)***
Average Purchase Price	-1.27(0.08)***	-1.49(0.17)***		-1.66(0.33)***	
Water Requirement (Low)* Yard size (0.26-0.40 acres)				0.38(0.11)**	
Saline Tolerant* Yard size (0.26-0.40 acres)				0.39(0.08)***	
Winterkill (Low)* Yard size (> 0.40acres)				0.26(0.19)**	
Saline Tolerant* Yard size (> 0.40acres)				0.31(0.08)	
Winterkill (Medium)* Age >45				-0.32(0.15)***	
Saline Tolerant* Age >45				-0.23(0.23)**	
Water Requirement (Low)*Female				0.23(0.15)**	
Water Requirement (Low)*White				0.52(0.11)**	
Water Requirement (Medium)*White				0.36(0.15)***	

Maintenance cost (Low)*White			0.26(0.14)***
Winterkill (Low)* (Income $75,000-$100,000)			0.48(0.19)**
Winterkill (Medium)* (Income $75,000-$100,000)			0.59(0.20)***
Winterkill (Medium)* (Income > $100,000)			0.48(0.27)*
Shade Tolerant* Hobbyist			0.27(0.11)**
Water Requirement (Medium)*Both			-0.001(0.20)*
Log-likelihood	-7026.19	-6607.11	-6792.33
Pseudo R^2	0.10	0.15	0.14
Sample size	1,179	1,179	1,179

***, **, and * Represents significance at 1% level, 5% level, and 10% level, respectively. Numbers in parentheses are standard errors.

Table 2.4. Parameter estimates of the latent class model.

Variables	**Willing household consumer**	**Reluctant household consumer**
	Estimates	**Estimates**
No Change	-1.27***	2.44***
	(0.10)	(0.21)
Lawn lost by winterkill	0.38***	1.30***
(Low vs High)	(0.05)	(0.16)
Lawn lost by winterkill	0.19***	0.55***
(Medium vs High)	(0.06)	(0.14)
Shade Tolerant	0.36***	0.84***
	(0.04)	(0.11)
Water requirement	0.93***	2.34***
(Low vs High)	(0.05)	(0.18)
Water requirement	0.47***	1.28***
(Medium vs High)	(0.05)	(0. 18)
Saline Tolerant	0.09**	-0.25**
	(0.04)	(0.11)
Maintenance cost (Low	0.03	0.57***
vs No change)	(0.05)	(0.12)
Maintenance cost	-0.30***	-0.63***
(High vs No change)	(0.05)	(0.14)
Average Purchase	-1.03***	-3.06***
Price	(0.10)	(0.27)
Demographics and attitudinal covariates	**Estimates**	
Constant	0.95***	
Hobbyist	0.62***	
Saver	0.17	
Both	0.22	
Age (<30)	0.45	
Age (>45)	-0.90***	
Income ($50,000-$74,999)	0.08	
Income ($75,000-$100,000)	0.05	
Income (>$100,000)	0.64*	
Class probability	0.67	0.33
Log likelihood	-6277.77	
Pseudo R^2	0.19	

***, **, and * Represents significance at 1% level, 5% level, and 10% level, respectively. Numbers in parentheses are standard errors.

Table 2.5. Fit statistic information of different models.

Models	Log Likelihood	No of Parameters	BIC	AIC	Pseudo R^2
Conditional Logit	-7026.19	10	7041.55	14062.38	0.10
Mixed Logit	-6607.11	19	6636.29	13233.23	0.15
Mixed Logit with interaction	-6792.33	75	6907.51	13659.65	0.14
Latent class model (2 class)	-6277.77	29	6322.31	12584.55	0.19
Latent class model (3 class)	-6091.77	48	6165.49	12231.54	0.22
Latent class model (4 class)	-6021.30	67	6124.19	12109.59	0.23
Latent class model (5 class)	-5959.19	86	6091.27	12004.38	0.23
Latent class model (2 class) (without covariates)	-6586.30	20	6617.01	13192.60	0.15
Latent class model (3 class) (without covariates)	-6485.14	30	6531.21	13000.27	0.16
Latent class model (4 class) (without covariates)	-6434.30	40	6495.73	12908.59	0.17
Latent class model (5 class) (without covariates)	-6388.10	50	6464.88	12826.19	0.18

The sample size is 1179 respondents.

Table 2.6. Willingness to pay for turfgrass attributes ($\$/ft^2$) for the latent class model (LCM).

Variables	**LCM** Willing Household Consumer	Reluctant Household Consumer	Probability Aggregated WTP
Lawn lost by winterkill (Low vs High)	0.37 (0.26-0.49)	0.42 (0.32-0.53)	0.39 (0.27-0.50)
Lawn lost by winterkill (Medium vs High)	0.19 (0.07-0.29)	0.18 (0.08-0.27)	0.18 (0.08-0.28)
Shade Tolerant	0.35 (0.26-0.44)	0.28 (0.20-0.35)	0.33 (0.24-0.41)
Water requirement (Low vs High)	0.90 (0.70-1.09)	0.77 (0.61-0.91)	0.86 (0.67-1.03)
Water requirement (Medium vs High)	0.46 (0.33-0.59)	0.42 (0.29-0.54)	0.45 (0.31-0.57)
Saline Tolerant	0.08 (0.01-0.16)	-0.08 (-0.15- -0.1)	0.03 (-0.04-0.09)
Maintenance cost (Low vs No change)	0.03[a] (-0.08-0.13)	0.19 (0.09-0.27)	0.08 (-0.01-0.17)
Maintenance cost (High vs No change)	-0.29 (-0.39- -0.18)	-0.21 (-0.31- -0.10)	-0.26 (-0.36- -0.16)

Willingness to pay measures is calculated with the Delta method of the Wald procedure contained within LIMDEP 10.0 N LOGIT 5.0. Numbers in parentheses are confidence interval at 5% level. [a] indicates that the Wald procedure resulted in insignificant willingness to pay value for this attribute.

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 5000 square foot lawn ($/ft^2)	$0.20	$0.40	

	Option A	Option B	Option C
I would choose	○	○	○

Figure 2.1. An example of the discrete choice experiment choice set.

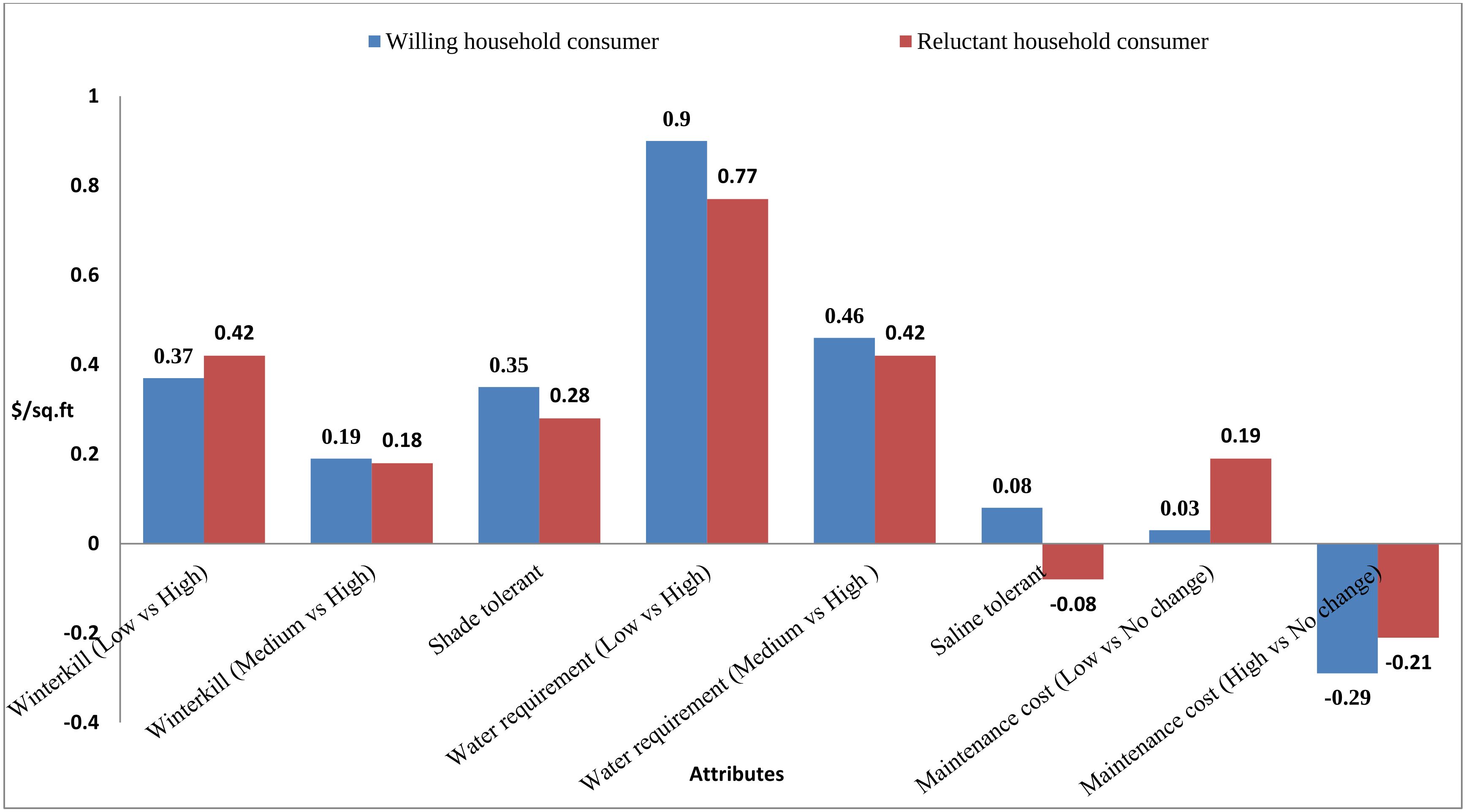

Figure 2.2. Marginal willingness to pay for turfgrass attributes for willing household consumer and reluctant household consumer.

CHAPTER III

PREFERENCE SHARES FOR TURFGRASS ATTRIBUTES: A COMPARISON OF DISCRETE CHOICE EXPERIMENT AND BEST-WORST METHOD

ABSTRACT

Prioritizing the attributes may vary by the methods of choice experiments and for different types of products. This study compares preference shares for turfgrass attributes in five states (North Carolina, Florida, Georgia, Oklahoma, and Texas) in the southeastern and mid-southern United States using the discrete choice experiment (DCE) and the best-worst method (BWM). An online survey was conducted and a mixed logit model was used to determine the homeowners' relative preferences for turfgrass attributes. The result indicates that the most preferred attribute using either of the methods was low maintenance cost. Although the relative importance by the DCE and the BWM is statistically different, both methods yield a similar preference ordering for low maintenance, drought tolerant, and saline tolerant turf, while different ordering for shade tolerant and low purchase price turf. This study is one of the first to use relative importance (preference share) scales to compare the DCE and the BWM from the homeowners' perspective for the turfgrass attributes.

Introduction

Determining consumers' preferences for product characteristics has gained major attention in decision making and public policy. Prioritizing the importance for goods is necessary to understand and manage the outcomes of research in product development. Developing and releasing a product depends on the comparative importance consumers put for that product compared to other products with similar characteristics developed over years and decades of research. Public preferences for different products or the attributes of a product are usually elicited by direct or indirect valuation methods. The most popular and relevant method to elicit the consumers' preferences in hypothetical scenarios are discrete choice experiments (DCE) and ranking methods such as best-worst method (BWM) (Bleichrodt, 2002).

The DCE is a stated preference method which allows us not only to analyze consumers' preferences, but also to determine the shares of preferences of the attributes used in the experiment. The share of preference indicates the relative importance of the attributes used in the study that ranges from 0 to 100 in percentage, shares of preference for the attributes sums up to 100 percent. Preference shares of attributes can be determined by measuring the utility (part worths) of attributes in various combinations of choices made (Louviere and Woodworth, 1983; Louviere, Hensher and Swait, 2000). The DCE is an indirect method of measuring utility or preference (Louviere and Islam, 2008) and has been widely used for environmental policy and other public policy decision making.

The BWM, also known as Maximum Difference Scaling, is an alternative preference elicitation method. The BWM is a direct scaling procedure that directly measures the subjective dimension, such as “degree of importance” or “degree of interest” (Auger, Devinney and Louviere, 2004). This method assumes respondents are able to identify the best or worst and the most or least important options from the provided list of choices and analyses the respondent’s perceptive process of picking two items that are the farthest apart on scaling measurement. An interval scale of the items based on aggregate response gives ordinal ranking to variables used in the study (Louviere and Woodworth, 1991). The BWM is relatively simple method that yields coefficients for each attribute which can be used to determine the share of preference as the forecasted probability of the attributes.

Both DCE (Ryan and Gerard, 2003; Cheragi-Sohi et al., 2008; Lancsar and Louviere, 2008) and BWM (Goodman and Lockshin, 2005; Flynn et al., 2007, Lusk and Briggeman, 2009) methods have widely been used to determine the preference share of attributes separately. However, few previous studies exist that actually compare the preference share of attributes using both DCE and BWM (Potoglou et al., 2011; Whitty et al., 2014). Potoglou et al. (2011) and Whitty et al. (2014) compared the parameter estimates from the DCE and BWM methods. However, the current study compares the two methods on the preference share scale for the attributes. Although comparative DCE-BWM studies have been performed on the health technology service sector (Potoglou et al., 2011 and Whitty et al., 2014), there are no studies that focus on the comparison of the DCE and BWM 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. Turfgrass being a pervasive feature of the urban landscape in the United States, it covers larger area than any other irrigated crops in the urban landscape. In the context of weather variability, climate change, drought, and reduced water supplies, lawn maintenance has become a challenge. During drought and water shortage municipalities often prohibit the use of potable freshwater in the turfgrass landscape considering it a low priority (Kjelgrcn, Ruppi, and Kilgren 2000). This has led to the use of low quality water like effluent or reclaimed water for turf irrigation. In addition, other stress related problems like excessive shade, winterkill, and high maintenance in urban landscape drive the demand for more innovative turf types which can tolerate stresses. However, turfgrass breeders are uncertain of consumers' preferences for these improved cultivars. This study on how consumers' prioritize several turf cultivars will contribute to research progress to focus on development and marketing of most preferred cultivars to meet the household consumers' demand. The study on consumers' preferences for improved turf cultivars will help to connect the research progress and turfgrass market to yield economic surplus. Thus, the specific objectives of this study are to identify the preference shares for different turfgrass attributes from homeowners of five states (Florida Georgia, North Carolina, Oklahoma, and Texas) in the mid-southern and southeastern United States and to compare and contrast results from the DCE and the BWM.

Methodology

Homeowners Survey

To determine the share of preference homeowners' place to the attributes of turfgrass, we utilize recent advances on the BWM and the DCE. In both DCE and BWM, respondents were presented with a number of profiles of turfgrass attributes. Attributes for the profiles were initially derived from a literature review on preferences of turfgrass attributes for lawn (Yue, Hugie, and Watkins, 2012) and also with a consultation and agreement with the panel of breeders, physiologists, and other experts working on turfgrass industry.

A web based online survey was conducted with 1,179 homeowners from Georgia, Oklahoma, North Carolina, Florida, and Texas in November 2013. Each survey includes the six BWM questions with each question containing three different options for different turfgrass attributes, the six DCE questions with each containing three different options 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 1,179 complete surveys were received from the survey programmed by Qualtrics collaborating with a sample of respondents obtained from panel company Survey Sampling International.

Survey Design

Discrete Choice Experiment. The experimental design for the DCE is similar to Louviere, Hensher, and Swait, 2000. Six measurable attributes associated with turfgrass adoption ranging from 2 to 4 levels were identified. Description of the attributes and levels, and number of levels are provided in Table 3.1. These attributes and levels created $4^1 \times 3^3 \times 2^2 = 432$ possible combinations of attributes. However, a fractional factorial design that maximizes D-efficiency was determined and used. The fractional design consisted of 18 choice sets of turfgrass attributes profiles with D-efficiency of 96.4%. Three surveys each containing six different sets of the DCE choice set were determined. In each DCE choice set, there were three different options (A, B, and C). Options A and B contain the combination of turfgrass attributes and its different levels (turfgrass attributes profiles), and option C represented the status quo or a no change option. For each choice set, were asked to choose one of the three profiles or options. An example of the DCE choice set is provided in Figure 3.1.

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 six attributes of turfgrass (Table 3.2.). 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, USA) which 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. An example of the BWM choice set is provided in Figure 3.2.

Econometric Model

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

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

(1) $$U_{ij} = \boldsymbol{X}_{ijs}\boldsymbol{\beta}_{ijs} + \varepsilon_{ijs}$$

where $\boldsymbol{X}_{ijs}$ is the vector of the turfgrass attributes that describes and represents the characteristics of alternative j, $\boldsymbol{\beta}_{ijs}$ is the parameter vector of attributes of turfgrass, ε_{ijs} is independent and identically distributed (IID) error term that follows a type I extreme value distribution. Allowing model 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 modelling a distribution of β_i as:

(2) $$\boldsymbol{\beta_{ik}} = \boldsymbol{\beta}_k + \boldsymbol{\sigma}_k \eta_{ik}$$

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 Equation (2) where η_{ik} is an error term with distribution f (η_{ik}). Hence, $\boldsymbol{\beta_{ik}}$ is a random variable with distribution f($\boldsymbol{\beta_{ik}}$), mean $\boldsymbol{\beta_k}$ and standard deviation $\boldsymbol{\sigma}_k$. 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 simulated log likelihood function. The distribution simulation was based on 200 pseudorandom Halton draws.

In the DCE experiment, we can characterize the share of preference or relative importance for each attribute. This 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 add to 100 percent. The share of preference for each attribute is calculated as follows:

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

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. The share of preferences are estimated on the mean of the equation (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 equation (2). After the mixed logit model 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. This Bayesian calculation allows for a conditional distribution on 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 of importance and the true level of importance is $\mathrm{I}_{\mathrm{it}} = \lambda_t + \varepsilon_{it}$, where ε_{it} is an error term with an extreme value distribution (Lusk and Briggeman, 2009; Finn and Louviere, 1992). The probability that consumer chooses to maximize the distance between item *t* and *k*, that is 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. This takes a conditional logit form as follows:

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

where *m* are the pair of attributes seen, but not chosen as the maximizing pair. The λ_t

is estimated by maximum likelihood estimation based on probability statement in (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_t represents the importance of attribute T relative to some attributes that were normalized to zero to prevent the "dummy variable trap." In the mixed logit form the relative importance of each individual can be identified as:

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

where $\bar{\lambda}$ and σ are the mean and standard deviation of λ_t 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 was also based on 200 pseudorandom Halton draws.

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

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

Similar to the DCE, the share of preferences for the BWM are also estimated on the mean of the equation (6) evaluated in 1000 random draws. The random draws are generated (following a normal distribution) using the estimated means and standard deviations of the MLM as in equation (5).

Comparing the preference share in the DCE and the BWM. The preference shares for each attribute obtained from the DCE and the BWM are compared if the difference in preference share between two methods is statistically different. The preference ordering of the attributes among 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 1,179 respondents are shown in Table 3.3. The majority of respondents consist of people more than 45 years. The mean age of respondents across states ranged from 49 to 61 years, with standard deviation of about 15 years. The mean annual household income of respondents ranged from $56,991 in Oklahoma to $79,604 in Texas, and their mean income is higher than the state's average. Median household income is $45,339 in Oklahoma, $46,334 in North Carolina, $46,956 in Florida, $49,179 in Georgia, and $51,900 in Texas (US Census, 2013). The majority of the respondents are female in all states except Oklahoma. Mean lawn sizes of the respondents' ranged from 0.35 to 0.49 acres across states, indicating that respondents had a larger lawn size in general. The average lawn size in the US varies from state to state, ranging from 0.06 acre in Washington D.C to 0.51 acre in Georgia (Chapman, 2015).

Results and Discussions

Parameter Estimates from the Mixed Logit

Discrete Choice Experiment. The estimates of the variables for the DCE are given in Table 3.4. 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 winter kill 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 pooled data. These coefficient estimates are used to calculate the preference share of each attributes for the homeowners.

The shares of preference for the attributes using the DCE are provided in Table 3.5. 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 requiring turf (18.8%), while 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 their lawns using the DCE among individual states are slightly different but in each state three most preferred turfgrass attributes for homeowners are low average maintenance cost, shade tolerance, and water conserving turf, while 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, while winterkill tolerant turf is more preferred than saline tolerant turf in Oklahoma, North Carolina, and Texas. The preference share for low maintenance turf ranged from 42.4% (Georgia) to 59.1% (North Carolina), shade tolerant turf ranged from 16.5% (Florida) to 25.7% (Georgia), water conserving turf ranged from 15.5%

(Oklahoma and North Carolina) to 22.1% (Texas), saline tolerant turf ranged from 1.2% (North Carolina) to 14.8% (Georgia), and winterkill attribute ranged from 1.1% (Georgia) to 5.4% (Oklahoma). The preference share for the average purchase price attribute is insignificant and less than unity for all states.

Best-Worst Method. In the analysis of the BWM, one variable (winterkill tolerant) is dropped to avoid perfect collinearity in the variables. The parameter estimates of the BWM are provided in Table 3.6. 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 pooled data. The parameter estimates of the BWM are used to estimate preference share of each attribute through forecasted probabilities as in (7). Pooling all states together, the most preferred attribute using the BWM is low average maintenance cost (44.9%) followed by drought tolerant (25.8%) and low average purchase price (13.1%), while least preferred attributes are saline tolerant (6.4%) and shade tolerant turf (9.8%) (Table3.7). The drought tolerant attribute is the most preferred attribute in Texas, while low maintenance cost is the most preferred attribute in other four states. The preference share for low maintenance turf ranged from 32.5% (Texas) to 50.6% (North Carolina), drought tolerant turf ranged from 18.6% (Georgia) to 43.4% (Texas), low average purchase price of turf ranged from 9.7% (Texas) to 15.7% (North Carolina), shade tolerant attribute ranged from 7.3% (Florida) to 13.8% (Georgia), and saline tolerant attribute ranged 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 (Fernando et al., 2015, Svoboda, 2014). Parts of North Carolina, Texas, and Georgia are subject to salinity. The importance of cold hardiness at North Carolina and Oklahoma are based on latitude and USDA cold hardiness zone as winter kill is important factor in these states in terms of bermudagrass and zoysaigrasses (Martin, 2015).

Comparison of Preference Share of Attributes between the DCE and the BWM

A pairwise comparison of differences in the share of preferences of turfgrass attributes between the DCE and BWM is presented in Table 3.8. The result shows that the preference levels by the DCE and the BWM are statistically different. However, out of 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 (Figure 3.3). In Florida, Georgia, Oklahoma, and North Carolina, the most preferred attribute for homeowners using both methods is low maintenance turf (Figures 3.4, 3.5, 3.6, and 3.7, respectively) The most notable difference between two methods is observed with shade tolerant and average purchase price attribute (Table 3.8). The difference is relatively high for these two attributes in each state. The shade tolerant attribute is one of the highly valued attributes using the DCE, but it is one of the least preferred attribute using the BWM. In addition, the average purchase price is the least preferred attribute in the DCE, while it is mostly ranked the third valued attribute in the BWM. The possible reason for this might be due to insignificant parameter estimate for average purchase price attribute in the DCE. In Texas, the difference in the preference share for the drought tolerant attribute is high as the respondents valued the drought tolerant attribute to be more preferred in the BWM, while low maintenance cost attribute is valued more in the DCE (Figure 3.8). Though the preference share is statistically different between two methods, the ordering in the share of preference was similar except for average purchase price and shade tolerant attribute. Previous studies have reported similarity (Potoglou et. al, 2011) as well as differences in estimate of attributes from these two methods (Whitty et al., 2014). Similar to this study, Whitty et al. (2014) also reported differences between two methods but similar ordering of the attributes.

Homegeneity in preference shares of the attributes among states and 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 to the BWM which might support the use of the DCE. Thus, there is no clear indication of one method being better over 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 least probability of bias in the rating scale (Cohen and Markowitz, 2002). However, studies also suggest that the DCE is more feasible and reliable method to elicit the preferences since the BWM becomes complicated due to 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 preference share of turfgrass attributes using the DCE and the BWM in five states (Florida, Georgia, North Carolina, Oklahoma, and Texas) of the southeastern and mid-southern 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. Although the preference share by the DCE and the BWM is statistically different, both methods yield a similar direction of preference ordering for low maintenance, drought tolerant, and saline tolerant turf. However, the preference ordering for shade tolerant and low purchase price turf is different in two methods. The difference in the preference level between two methods indicates bias in the DCE due to the use of hypothetical scenario and differences in respondents' inferences for the attributes that were omitted or not seen in the choice sets, affecting both means and variances of the variables (Islam, Louviere, & Burke, 2007). The statistical difference between two methods might also be due to two distinct choice tasks. In the DCE, respondent chose among three complete set of profiles for lawn, while in the BWM, they chose among three to six different turfgrass attributes. Implementation of a similar choice task for both methods could be helpful to examine if these two methods give similar preference in that context.

In context to this study, the DCE could be more appropriate for application for turf wholesalers due to inclusion of an actual price variable and letting respondents indirectly choose an option and make tradeoff among a set of scenarios. In addition, the BWM may not perform well in priority setting context for applied marketing studies (Whitty et al., 2014). However, the ambiguity about methods warrants further studies about the selection of the best method. The large standard deviations in the preference share of attributes indicate that there was heterogeneity in the relative importance of turfgrass attributes. The more complex methods such as latent class mixed models could be used in further studies to address the sources of heterogeneity. A segment of population might respond similarly to both methods while others might respond differently.

Overall, this study provides an early insight on the use of preference scales to compare the results of the DCE and the BWM from the homeowners' perspective on preferring the stress tolerant turfgrass attributes. This study gives a notable outcome in reconfirming the findings from Yue, Hugie, and Watkins (2012) that people value low maintenance turf the most using both methods. In addition, drought tolerant turf is also in homeowners' high priority list. Thus, this study provides framework for the turfgrass researchers and producers to invest and expand outreach on desirable turfgrass attributes for the homeowners.

References

Auger, P., T. M. Devinney, and J. Louviere. “Consumer Social Beliefs: An International Investigation Using Best-Worst Scaling Methodology.” Unpublished Working Paper (2004).

Bleichrodt, H. “A New Explanation for the Difference between Time Trade-off Utilities and Standard Gamble Utilities.” *Health Economics* 11,5(2002):447-56.

Chapman, E. Ground Maintenance. Available at http://grounds-mag.com/mag/grounds_maintenance_lawn_size/. verified on May 7, 2015.

Cheraghi, S., A.R. Hole, N. Mead, R. McDonald, D. Whalley, P. Bower, and M. Roland. “What Patients Want From Primary Care Consultations: A Discrete Choice Experiment to Identify Patients’ Priorities.” *The Annals of Family Medicine* 6,2(2008):107-15.

Cohen, S.H., and P. Markowitz. “Renewing Market Segmentation: Some New Tools to Correct Old Problems.” Paper presented at the ESOMAR 2002 Congress Proceedings 2002.

Fernando, N., R. fu, R.S. Solis, R.E. Mace, Y. sun, B. Yang, and B.Pu. “Early Warning of Summer Drought Over Texas and the South Central United States: Spring Conditions as a Harbinger of Summer Drought .”Technical Note 15-02, 2015. Texas Water Development Board.

Finn, A., and J.J. Louviere. “Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety.” *Journal of Public Policy and Marketing* 11(1992):12–25.

Flynn, T.N., J.J. Louviere, T.J. Peters, and J. Coast. “Best–Worst Scaling: What it Can Do for Health Care Research and How to Do it.” *Journal of Health Economics* 26,1(2007):171-89.

Goodman, S.P., L. Lockshin, and E.Cohen. “Best-Worst Scaling: A Simple Method to Determine Drinks and Wine Style Preferences.” *International Wine Marketing Symposium*. 2005.

Hensher, D.A., and W.H. Greene. “The Mixed Logit Model: The State of Practice.” *Transportation* 30,2(2003):133-76.

Kjelgrcn,R., L.Ruppi, and D. Kilgren. “Water Conservation in Urban Landscapes.” *HortScience* 35, 6(2000):1037-40.

Lancsar, E., and J. Louviere. “Conducting Discrete Choice Experiments to Inform Healthcare Decision Making.” *Pharmacoeconomics* 26,8(2008):661-77.

Louviere, J.J., and G. Woodworth. “Design and Analysis of Simulated Consumer Choice or Allocation Experiments: an Approach Based on Aggregate Data.” *Journal of Marketing Research*(1983):350-67.

Louviere, J.J., and G.G. Woodworth. “Best-Worst Scaling: A Model for the Largest Difference Judgments.” University of Alberta: Working Paper (1991).

Louviere, J.J., and T. Islam. “A Comparison of Importance Weights and Willingness-To-Pay Measures Derived From Choice-Based Conjoint, Constant Sum Scales and Best–Worst Scaling.” *Journal of Business Research* 61,9(2008):903-11.

Louviere, J.J., D.A. Hensher, and J.D. Swait “Stated Choice Methods: Analysis and Applications.” Cambridge University Press (2000).

Lusk, J.L., and B.C. Briggeman. “Food Values.” *American Journal of Agricultural Economics* 9,1(2009):184-96.

Martin, D. Expert Communication, Professor and Plant Breeder, Oklahoma State University (July 22, 2015)

McFadden, D., and K.Train. “Mixed MNL Models for Discrete Response.” *Journal of Applied Econometrics* 15,5 (2000): 447-70.

Orme, B. “Interpreting the Results of Conjoint Analysis.” *Getting Started with Conjoint Analyis: Strategies for Product Design and Pricing Research* (2010): 77-88.

Potoglou, D., P. Burge, T. Flynn, A. Netten, J. Malley, J. Forder, and J.E. Brazier. “Best–Worst Scaling Vs. Discrete Choice Experiments: An Empirical Comparison Using Social Care Data.” *Social Science & Medicine* 72,10(2011):1717-27.

Ryan, M., and K. Gerard. “Using Discrete Choice Experiments to Value Health Care Programs: Current Practice and Future Research Reflections.” *Applied Health Economics and Health Policy* 2,1 (2003):55-64.

Svoboda, M. Oklahoma Drought Monitor Map (May, 2014). Available at: http:// www.mesonet.org/index.php/agriculture/map/agriculture essentials/drought/oklahoma drought monitor map. verified in July 16, 2015.

Train, K. 2003. Discrete Choice Methods with Simulation. Cambridge, UK: Cambridge University Press.

Whitty, J. A., J. Ratcliffe, G. Chen, and P.A. Scuffham. 2014. “Australian Public Preferences for the Funding of New Health Technologies A Comparison of Discrete Choice and Profile Case Best-Worst Scaling Methods”. *Medical Decision Making* 34(2014):638-54.

Xie, F., E. Pullenayegum, K. Gaebel, M. Oppe, and P. F. M. Krabbe. “PIH39 Eliciting Preferences to the EQ-5D-5L Health States: Discrete Choice Experiment or Multiprofile Case of Best-Worst Scaling.” *Value in Health* 15,4(2012):A198-A199.

Yue, C., K. Hugie and E. Watkins. “Are Consumers Willing to Pay More for Low-Input Turfgrasses on Residential Lawns? Evidence from Choice Experiments.” *Journal of Agricultural and Applied Economics* 44 (2012):549.

Table 3.1. Turfgrass attributes and levels for the discrete choice experiment.

S.No.	**Attributes**	**Attribute Levels**	**Number of levels**
1	Lost lawn area to winter kill (50% probability)	0%, 20%, 40%	3
2	Shade tolerant	Yes , No	2
3	Watering your lawn (gallons/month)	Low (20,000 gallons), Medium (40,000 gallons), High (60,000 gallons)	3
4	Sod tolerant 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 5000 square foot ($\$/ ft^2$)	\$0.20, \$0.40, \$0.60, \$0.80,	4

Table 3.2. Turfgrass attributes for the best worst method.

S.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 require 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 ($\$/ ft^2$)

Table 3.3 Summary of the demographics of the respondents.

States	Age (Years)		Household Income		%	Lawn Size (acres)	
	Mean	Std. Dev.	Mean	Std. Dev.	Female	Mean	Std. Dev.
All States	51	15	$67,455	$48,033	53%	0.52	0.45
Florida	53	15	$65,693	$48,612	38%	0.37	0.35
Georgia	49	15	$70,258	$54,534	45%	0.62	0.46
Oklahoma	50	14	$56,991	$38,713	61%	0.57	0.49
North Carolina	61	14	$67,624	$49,770	46%	0.66	0.47
Texas	49	14	$79,604	$45,073	38%	0.39	0.36

Table 3.4. Parameter estimates for the discrete choice experiment.

Parameters	All States Estimate	Florida Estimate	Georgia Estimate	Oklahoma Estimate	North Carolina Estimate	Texas Estimate
Lawn Area Lost to Winter Kill	0.001	0.004	0.001	-0.005*	0.001	0.003
	(0.001)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
	[-0.001]	[-0.001]	[-0.001]	[-0.002]	[-0.001]	[-0.001]
	(0.053)	(0.116)	(0.105)	(0.089)	(0.124)	(0.105)
Shade Tolerant	0.757***	0.767***	0.992***	0.888***	0.683***	0.561***
	(0.047)	(0.119)	(0.152)	(0.121)	(0.113)	(0.089)
	[0.006]	[0.008]	[0.051]	[0.005]	[-0.001]	[-0.002]
	(1.623)	(4.004)	(2.730)	(3.203)	(3.915)	(3.394)
Water Requirement (per 1000 gallons)	-0.016***	-0.024***	-0.016***	-0.012***	-0.012***	-0.015***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.0001]	[-0.0001]	[-0.001]	[-0.001]	[-0.001]	[0.0001]
	(0.034)	(0.075)	(0.058)	(0.070)	(0.081)	(0.073)
Saline Tolerant	0.133***	0.410***	-0.141	0.158*	0.038	0.089
	(0.042)	(0.115)	(0.155)	(0.087)	(0.101)	(0.085)
	[0.009]	[-0.009]	[-0.788]	[-0.004]	[0.004]	[-0.001]
	(1.064)	(2.516)	(0.699)	(2.064)	(2.53)	(2.201)
Average Maintenance Cost	-0.021***	-0.021***	-0.015***	-0.027***	-0.025***	-0.015***
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
	[-0.072]***	[0.107]***	[0.065]	[-0.077]***	[-0.073]	[0.052]
	(0.006)	(0.016)	(0.015)	(0.013)	(0.015)	(0.012)
Average Purchase Price	0.002	0.003	-0.001	-0.001	-0.002	0.002
	(0.091)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.007]	[-0.001]	[-0.0003]	[-0.001]	[-0.001]	[-0.001]
	(0.801)	(0.017)	(0.020)	(0.015)	(0.020)	(0.018)
Sample Size	1179	228	206	295	203	247
Log likelihood	-7430	-1414	-1271	-1835	-1263	-1572
Pseudo R^2	0.132	0.163	0.155	0.160	0.124	0.102

*** and * Represents significance at 1% and 10%, respectively. Number in parentheses () are standard errors and number in brackets [ ] are standard deviations.

Table 3.5. Preference shares of attributes using part-worth of the discrete choice experiment.

	Share of Preference					
Attributes	**All States**	**Florida**	**Georgia**	**Oklahoma**	**North Carolina**	**Texas**
Lawn Area Lost to Winter Kill	0.007	0.033	0.011	0.054	0.015	0.045
	[0.007]	[0.016]	[0.008]	[0.028]	[0.012]	[0.024]
Shade Tolerant	0.228	0.165	0.257	0.239	0.226	0.212
	[0.100]	[0.069]	[0.095]	[0.101]	[0.114]	[0.087]
Water Requirement	0.188	0.208	0.161	0.155	0.155	0.221
(per 1000 gallons)	[0.083]	[0.086]	[0.060]	[0.066]	[0.079]	[0.091]
Saline Tolerant	0.040	0.088	0.148	0.043	0.012	0.034
	[0.018]	[0.037]	[0.105]	[0.018]	[0.006]	[0.014]
Low Average Maintenance Cost	0.536	0.505	0.424	0.510	0.591	0.488
	[0.204]	[0.204]	[0.198]	[0.207]	[0.207]	[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]

Number in brackets [ ] are standard deviations.

Table 3.6. Parameter estimates from the best-worst method.

	All States	Florida	Georgia	Oklahoma	North Carolina	Texas
Parameters	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Shade Tolerant	-0.055	0.268***	-0.188*	-0.255***	-0.373***	1.595
	(0.037)	(0.219)	(0.101)	(0.095)	(0.104)	(0.193)
	[0.796]***	[0.018]	[-1.281]***	[1.409]***	[0.921]***	[-1.418]***
	(0.109)	(1.925)	(0.256)	(0.221)	(0.275)	(0.245)
Drought Tolerant	1.0254***	1.225***	0.468***	1.272***	0.479***	1.996***
	(0.057)	(0.116)	(0.092)	(0.146)	(0.102)	(0.229)
	[0.941]***	[0.765]***	[0.610]***	[-1.191]***	[0.794]***	[-1.526]***
	(0.104)	(0.218)	(0.299)	(0.229)	(0.276)	(0.259)
Saline Tolerant	-1.369***	0.148*	-1.826***	-2.430***	-1.923***	-1.334***
	(0.071)	(0.083)	(0.218)	(0.225)	(0.235)	(0.165)
	[1.786]***	[1.346]***	[-2.097]***	[1.504]***	[2.080]***	[1.979]***
	(0.111)	(0.184)	(0.303)	(0.241)	(0.313)	(0.277)
Low Average Maintenance	1.593***	2.131***	1.479***	1.663***	1.758***	1.595***
Cost	(0.080)	(0.185)	(0.182)	(0.178)	(0.216)	(0.192)
	[-1.340]***	[-1.246]***	[-1.652]***	[1.697]***	[-1.595]***	[-1.417]***
	(0.109)	(0.216)	(0.280)	(0.243)	(0.287)	(0.254)
Low Average Purchase Price	0.413*** (0.037)	0.842***	0.292***	0.174***	0.328***	0.475***
	[0.485]***	(0.088)	(0.083)	(0.084)	(0.093)	(0.091)
	(0.148)	[-0.585]***	[-0.386]	[-1.002]***	[-0.739]	[-0.571]
		(0.249)	(0.399)	(0.233)	(0.288)	(0.351)
Sample Size	1179	228	206	295	203	247
Log likelihood	-14076	-2821	-2491	-3191	-2342	-2889
Pseudo R^2	0.47	0.43	0.45	0.59	0.51	0.51

***,**, and * Represents significance at 1%, 5%, and 10%, respectively. Number in parentheses ( ) are standard errors and number in brackets [ ] are standard deviations.

Table 3.7. Preference shares of attributes using the best-worst method.

Attributes	**All States**	**Florida**	**Georgia**	**Oklahoma**	**North Carolina**	**Texas**
Shade Tolerant	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 Tolerant	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 Tolerant	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]

Number in brackets [ ] are standard deviations.

Table 3.8. Differences in preference shares for attributes between the discrete choice experiment and the best-worst method.

	All States	Florida	Georgia	Oklahoma	North Carolina	Texas
Attributes	**DCE-BWM**	**DCE-BWM**	**DCE-BWM**	**DCE-BWM**	**DCE-BWM**	**DCE-BWM**
Shade Tolerant	0.130**	0.092**	0.119**	0.134**	0.133**	0.119**
Drought Tolerant	-0.070**	-0.011**	-0.025**	-0.158**	-0.032**	-0.213**
Saline Tolerant	-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**

Notes: ** Represents significance at 5% level. A pairwise T-test shows a significant difference between two methods.

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 5000 square foot lawn **($/ft^2)**	$0.20	$0.40	

	Option A	Option B	Option C
I would choose	○	○	○

Figure 3.1. 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 characteristics 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	○

Figure 3.2. An example of the best-worst method choice set.

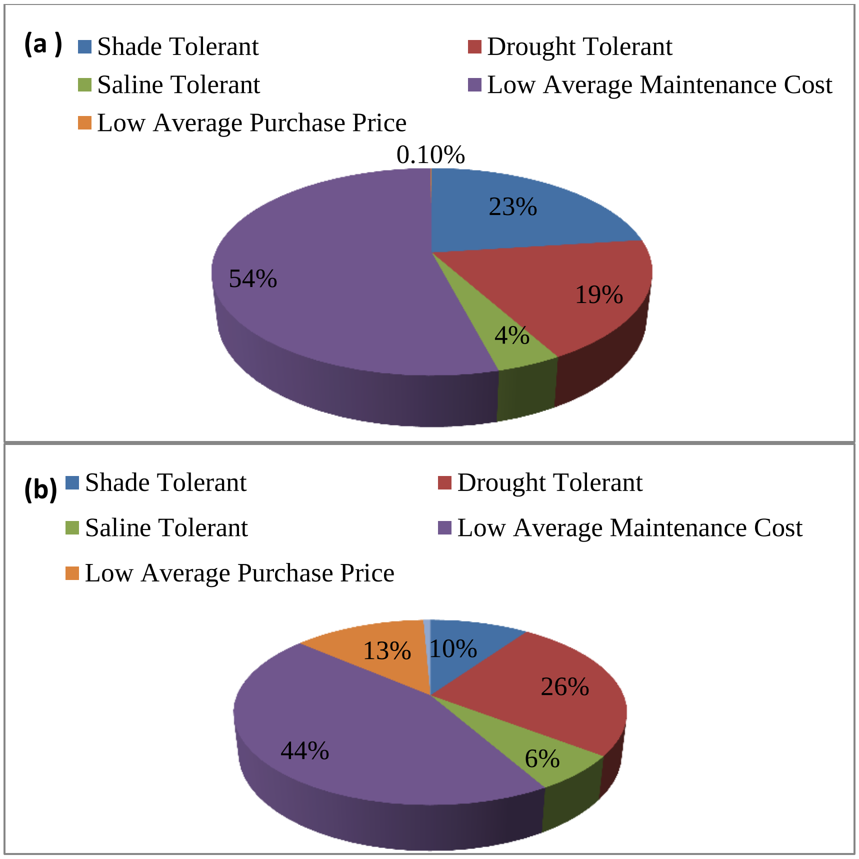

Figure 3.3. Preference shares for the attributes from (a) discrete choice experiment and (b) best-worst method for all states together.

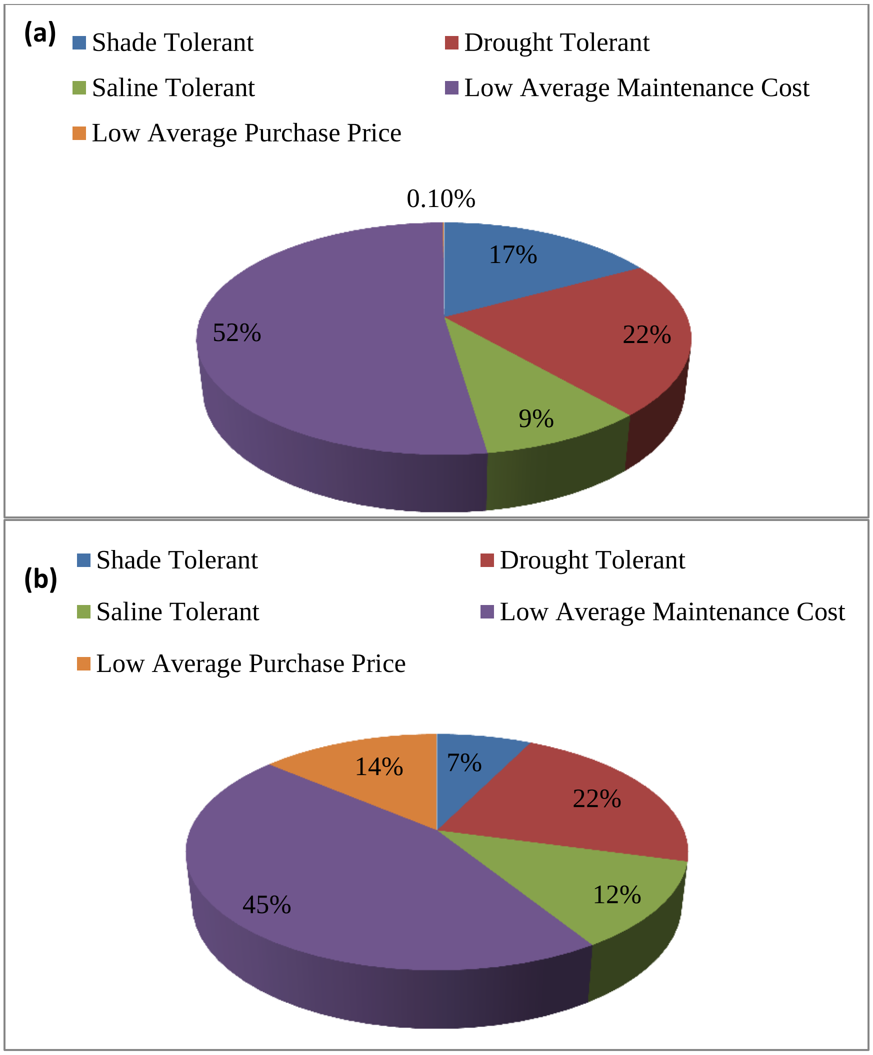

Figure 3.4. Preference shares for the attributes from (a) discrete choice experiment and (b) best-worst method for Florida.

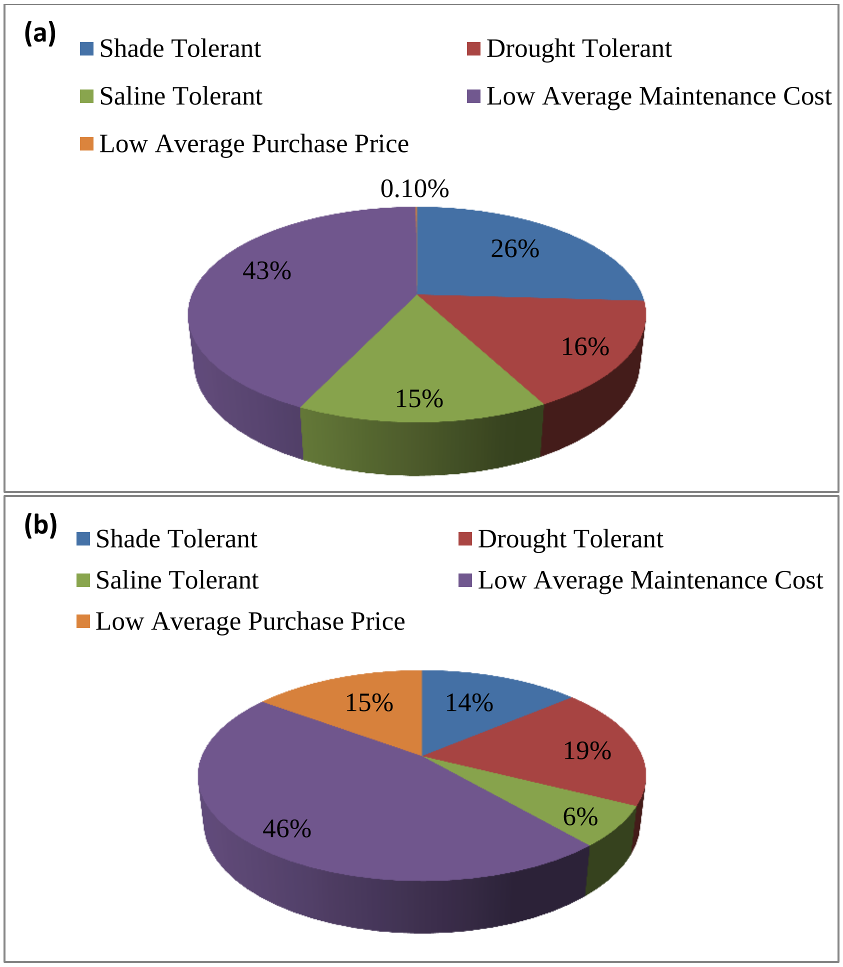

Figure 3.5. Preference shares for the attributes from (a) discrete choice experiment and (b) best-worst method for Georgia.

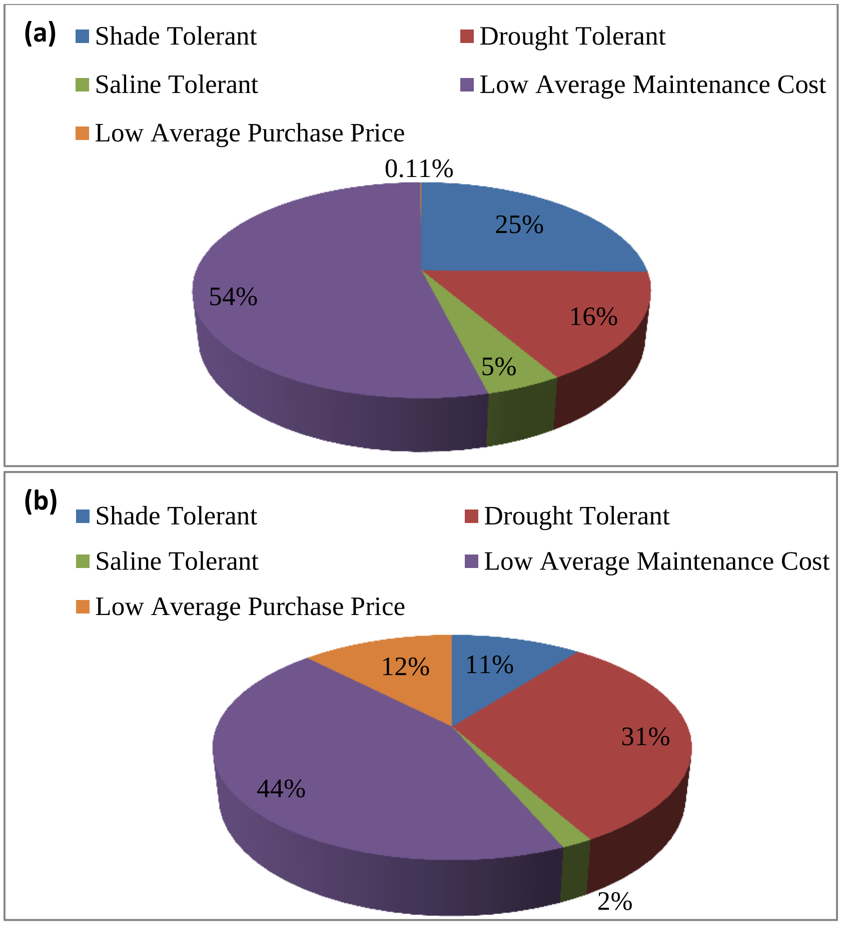

Figure 3.6. Preference shares for the attributes from (a) discrete choice experiment and (b) best-worst method for Oklahoma.

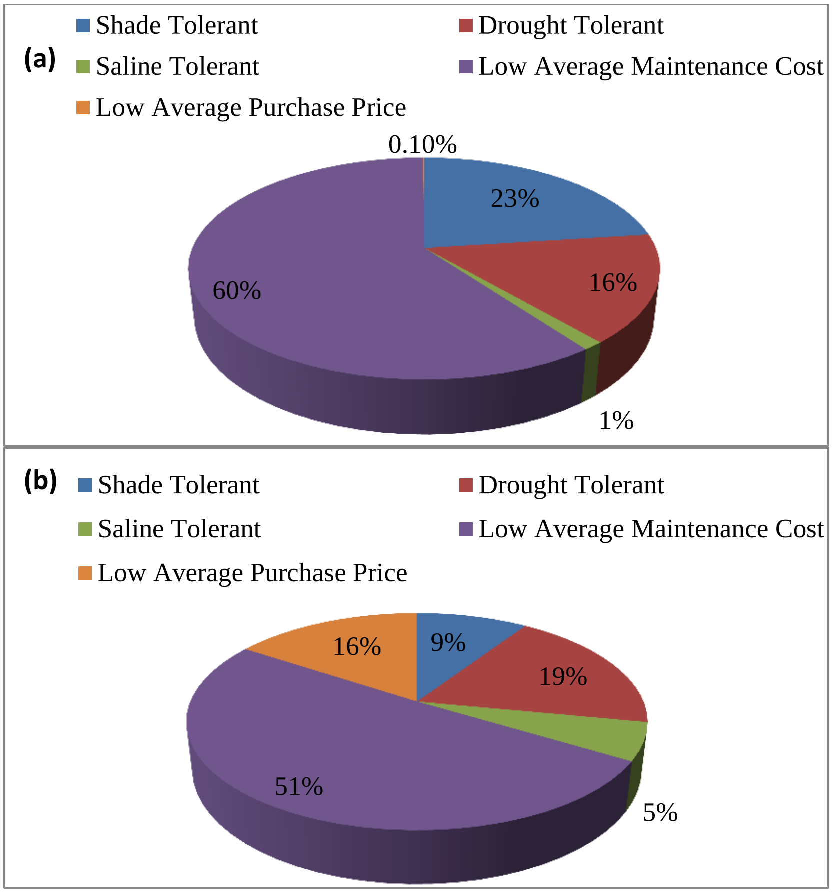

Figure 3.7 Preference shares for the attributes from (a) discrete choice experiment and (b) best-worst method for North Carolina.

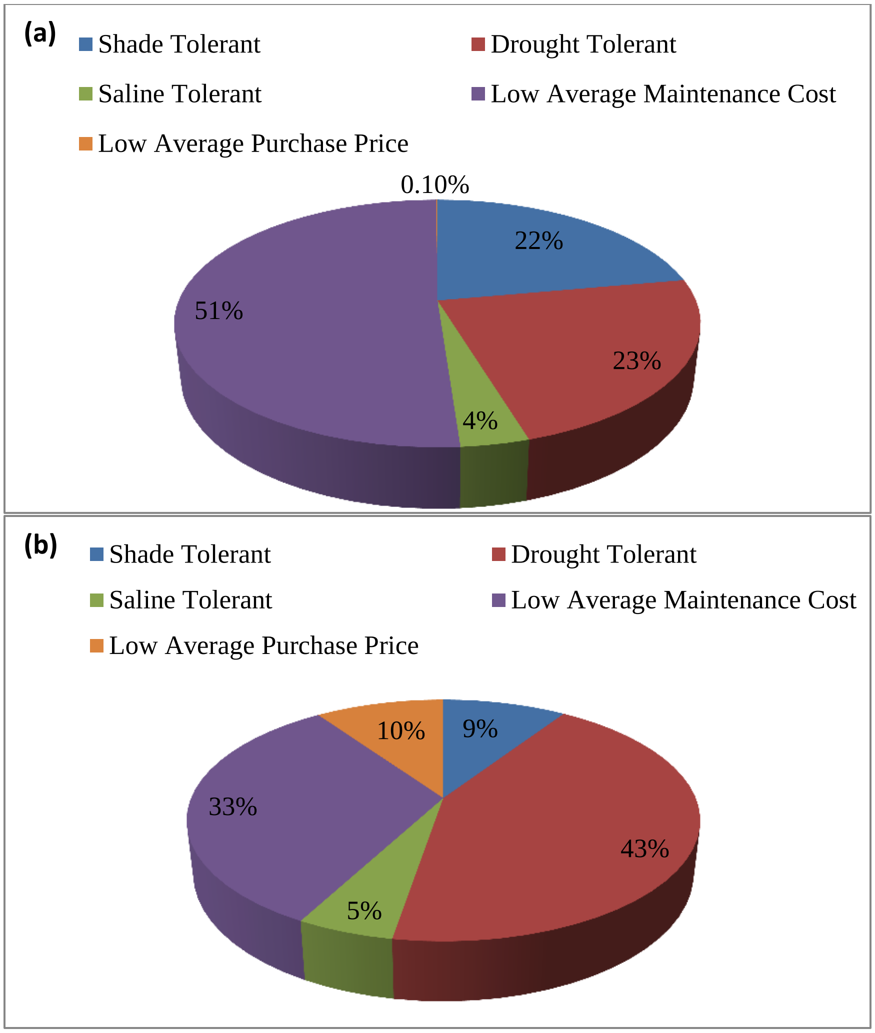

Figure 3.8. Preference shares for the attributes from (a) discrete choice experiment and (b) best-worst method for Texas

VITA

Monika Ghimire

Candidate for the Degree of

Doctor of Philosophy

Thesis: ESSAYS ON RESIDENTIAL WATER DEMAND AND CONSUMER PREFERENCES FOR TURFGRASS ATTRIBUTES

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in July, 2015.

Completed the requirements for the Master of Science in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in July, 2012.

Completed the requirements for the Bachelor of Science in Environmental Management at Pokhara University, Kathmandu, Nepal in 2008.

Experience:

Graduate Research Assistant, Department of Agricultural Economics, Oklahoma State University, August 2010 to July 2015.

Professional Memberships:

American Agricultural Economics Association