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Influence of COVID-19 on Consumer Preference for Turfgrass Attributes in the Southern United States

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***Abstract.* This study estimates the influence of the coronavirus disease 2019 (COVID-19) pandemic on consumer preferences for turfgrass attributes by analyzing data from two surveys conducted in Jan 2019 and Apr 2021. First, the study estimated a mixed logit model to account for individual heterogeneity in preferences. Subsequently, estimates of the willingness to pay (WTP) were compared between periods before and after the pandemic. To show the impact of consumers' risk attitudes with respect to climate change on their preference for turfgrass attributes, we re-estimated the model according to the risk attitude groups (i.e., risk-seeking vs. risk-averse). Finally, to examine how consumers' demographic characteristics and risk attitudes are related to their WTP for improved turfgrass attributes, we estimated a random-effect panel data model for each attribute. Our results showed that, overall, consumers' WTP increased during the COVID-19 pandemic. We also found that the WTP of risk-averse consumers were mostly higher than those of risk-seeking consumers during both time periods. Furthermore, the increase in the WTP observed among the risk-averse group was greater than the increase of the WTP of the risk-seeking group. Our findings imply that the demand for drought-tolerant and stress-resistant turfgrasses would increase with possible future climate changes and infectious disease outbreaks.**

Turfgrass is a natural plant that covers ∼2% of all continental land in the United States (Harrington 2016; Milesi et al. 2005). It is considered the most irrigated crop in the country because of its extensive use as vegetative cover for home lawns, golf courses, athletic fields, schools, parks, and roadsides (Stier et al. 2013). The unique characteristics of turfgrass make it an excellent plant for erosion control, oxygen production, heat and noise reduction, carbon dioxide absorption, and filtering of air and chemical pollution (Chawla et al. 2018; Qian et al. 2010). The demand for turfgrass species is driven by desirable characteristics such as drought tolerance (or level of water requirement), pest resistance, shade tolerance, winterkill (or stress) resistance, and low maintenance costs (Fry and Huang 2004). Although previous studies have linked some of these characteristics to consumer preferences to estimate the value of turfgrass attributes (Chung et al. 2018; Ghimire et al. 2016; Hildebrand et al. 2023; Hugie et al. 2012; Knuth et al. 2020), to the best of our knowledge, no study has examined the influence of the coronavirus disease 2019 (COVID-19) pandemic on consumer preference for these attributes.

The turfgrass industry, an extensive sector exceeding more than $40 billion in annual revenue and covering more than 50 million acres of land in the United States (Nature Shore 2023), plays a pivotal role in the nation's economy by providing employment opportunities and significantly boosting property values. However, the severe economic contraction caused by the pandemic disrupted various facets of this industry (Brosnan et al. 2020; Bulgari et al. 2021), potentially affecting the demand and, more specifically, consumer preferences, for turfgrass attributes. Because Americans' love for their lawns is unmatched globally (Bormann et al. 2001), understanding how the pandemic influenced turfgrass preferences is crucial to the future of the turfgrass industry.

This study assessed the influence of the COVID-19 pandemic on consumer preferences for turfgrass attributes, analyzed how consumer preferences change with consumers' risk perceptions, and examined how demographic factors affect consumer preferences for turfgrass attributes. This study extends previous studies in two ways. First, our study results elucidate how the pandemic has reshaped consumer demand for turfgrass attributes. Specifically, this study investigated whether consumers are more (or less) concerned about winterkill resistance, shade tolerance, water conservation, and low maintenance costs after the pandemic. Second, our study attempted to estimate the role of consumers' risk behaviors and demographic characteristics in driving changes in preferences, which should help researchers and stakeholders gain a better understanding of consumer demand for turfgrass cultivars, particularly in the context of major global crises.

To estimate consumer preferences, a mixed logit model was used in the willingness-to-pay (WTP) space during this study to account for individual heterogeneity in preferences. It has been argued that estimating the WTP directly in the WTP space rather than estimating marginal utilities yields results in better estimates in terms of stability when compared with estimates from the preference space models (Balcombe et al. 2009; Thiene and Scarpa 2009; Train and Weeks 2005).

The neoclassical theory of consumption serves as a fundamental framework for understanding how individuals make decisions about spending money and are guided by their preferences and budget constraints with the aim of maximizing their utility (Jehle and Reny 2011; Wooldridge 2012). This theory, combined with empirical analyses, emphasizes various factors that influence consumer demand such as taste, preference, advertising, income levels, prices, and availability of substitute goods (Yurievna 2022). The global pandemic resulted in profound changes in income levels, prices of goods and services, and a host of other factors that have been traditionally known to shape consumer preferences (Crayne 2020; Fisher et al. 2020). As a result, numerous studies have examined the influence of the pandemic on individuals' preferences for food, medication, environmentally friendly products, waste disposal, and various other commodities (Li et al. 2020; Schmitt et al. 2021; Sheth 2020; Sun et al. 2021). These studies suggested that new habits were likely to emerge after pandemic, leading to a shift in the demand for food choices and leisure activities (Powell et al. 2021).

In the context of the turfgrass industry, the demand for specific attributes, such as low maintenance costs, winterkill resistance, drought tolerance, and shade tolerance, can be particularly sensitive to these shifts (Joshi et al. 2018). Philocles et al. (2023) pointed out that large businesses facing closures or financial constraints during the pandemic were more likely to opt for low-input turfgrasses. Yue et al. (2021) found that promotion (advertisement), perceived benefits, accessibility, peer influence, and information availability are important factors that affect the demand for and adoption of turfgrass. Because many individuals experienced job losses or income reductions during the pandemic, these factors are likely to influence the demand for turfgrass attributes directly and/or indirectly.

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The pandemic disrupted various aspects of society, leading to both positive and negative impacts on sustainability indicators, including those related to air quality, water resources, soil health, energy efficiency, and food diversity (Geng et al. 2022; Khalaf et al. 2023). Specifically, the pandemic had a profound impact on consumer behavior, leading to shifts in demand for various retail consumer products, food choices, and even medical preferences (Kalam et al. 2022; Powell et al. 2021; Sheth 2020). Although certain goods experienced a surge in consumption and higher levels of WTP (Dangelico et al. 2022), others faced a decrease in demand (Bakar and Rosbi 2020; Campos-Vázquez et al. 2021), and some products and services experienced a mixed response from consumers (Ganslmeier et al. 2021; Wunsch et al. 2022). All these studies have given rise to a fundamental query: what was the impact of the COVID-19 pandemic on the demand for turfgrass attributes? As far as we know, no previous study has examined the change in consumers' preferences for turfgrass attributes before and after the COVID-19 pandemic, particularly within distinct consumer risk groups or demographic characteristics.

Previous studies have estimated the nonmarket value of various turfgrass attributes. For example, Ghimire et al. (2016) and Ghimire et al. (2019) evaluated homeowners' preferences for stress-resistant, low-maintenance, and low-cost turfgrass attributes using the discrete choice experiment and the best–worst method. Their results revealed that consumers ranked low-maintenance costs higher than the other attributes considered. Knuth et al. (2023) assessed the preferences of Floridian homeowners regarding high-level and low-level inputs of water and fertilizer. Their findings affirmed the presence of preference heterogeneity, indicating that homeowners expressed a higher WTP for turfgrass options with low-input attributes. Yue et al. (2012) estimated consumer preferences for attributes of nontraditional turfgrasses and considered aesthetic and maintenance attributes of turfgrass. Using an input–output model, Chung et al. (2018) analyzed the economic value of developing drought-tolerant and shade-tolerant warm-season turfgrasses, and the results indicated that the improved turfgrasses were expected to provide significant economic benefits for the southern states of the United States Ge et al. (2020) extended previous studies by considering the effect of survey participants' attention and showed that participants' attention levels and patterns affect consumers' WTP.

Consumers' risk attitudes have been incorporated in the demand analysis for various agricultural and food markets. Notably, these studies have illuminated the role of risk attitudes in shaping consumer demand for genetically modified food (Lusk and Coble 2005) and farmers' attitudes when determining farm production, investment, and management decisions (Ullah et al. 2015). Overall, these studies emphasized the need to consider risk attitudes when analyzing the evolving consumer demand behaviors. However, risk attitudes may not be the only determinant of changes in preference. Various studies have also suggested that demographic variables could affect consumer preferences. Liu et al. (2019) found that familiarity, age, education, income, and perceived risk play important roles in shaping consumers' WTP for technology. However, Lyford et al. (2010) found no significant impact of demographic factors on consumers' WTP for beef quality. These mixed results indicate that demographic variables may not be significant determinants in some specific contexts or for particular products. Although factors like sex, race, age, education, income, and perceived risk can play pivotal roles in determining the WTP for certain goods, their effects may not always be uniform across different settings or product categories.

To the best of our knowledge, no previous study has analyzed the effect of the COVID-19 pandemic on consumer preferences for turfgrass attributes according to risk behavior, particularly for low-input, drought-tolerant, and stress-resistant turfgrasses. Therefore, filling the gap in the literature is crucial because of the significant impact of the COVID-19 pandemic on consumer behaviors and preferences across various commodities that are already found in the literature. The global pandemic affected almost every industry in the economy, and many industries have not yet fully recovered from its effects. By analyzing changes in consumer preferences for turfgrass attributes because of COVID-19, we aimed to help breeders, producers, marketers, and policymakers gain a better understanding of the impact of the pandemic on economic values of newly developing turfgrasses.

Materials and Methods

To estimate changes in consumer preferences for turfgrass attributes following the COVID-19 pandemic, we used a mixed logit model in the WTP space. We decided to estimate the mixed logit model in the WTP space because of two reasons. First, as stated, the WTP space estimation provides more stable estimates than those resulting from the preference space estimation. Second, it is more convenient than the preference space estimation, especially when differences in the WTP need to be tested. During our study, changes in the WTP before and after the COVID-19 pandemic were tested. Using the WTP estimated from the mixed logit model, we calculated the preference shares of each attribute to show how respondents' rankings of these attributes changed after the outbreak of COVID-19. Finally, a panel data analysis was conducted to estimate the effect of demographic factors and risk attitudes on consumer preferences before and after the pandemic.

Mixed logit model. A mixed logit model was used instead of the conditional model logit model because the mixed logit model accounts for individual heterogeneity in preferences and overcomes the independence of irrelevant alternatives assumption (Hensher et al. 2005). Additionally, the random parameter model captures individual-specific differences that may affect the likelihood of structural changes. Then, an individual's data-generating process for our survey can be specified as follows:

$$U_{ij} = \boldsymbol{X}_{ij}\boldsymbol{\beta}_i + \varepsilon_{ij} \qquad [1]$$

where U_{ij} is the utility that individual i derives from choosing alternative j, $\boldsymbol{X}_{ij}$ is a vector of all levels of attributes that relates the individual i to the alternative j, $\boldsymbol{\beta}_i$ is a vector of parameters representing the individual's preference, and ε_{ij} is the random error term that is independently and identically distributed. The probability that the individual i chooses the j^{th} alternative from choice set T is as follows:

$$P(j) = P(\boldsymbol{X}_{ij}\boldsymbol{\beta}_i + \varepsilon_{ij} \geq \boldsymbol{X}_{ik}\boldsymbol{\beta}_i + \varepsilon_{ik;}\forall\ k \in T) \qquad [2]$$

Eq. [1] can be estimated using a mixed logit model that accounts for individual differences.

The deterministic part of individual i choosing option j can be specified as:

$$\begin{aligned} v_{ij} = {} & \beta_1 ASC_i + \beta_2 Winterkill_{Mij} \\ & + \beta_3 Winterkill_{Lij} + \beta_4 Shade_{ij} \\ & + \beta_5 Water_{Mij} + \beta_6 Water_{Lij} \\ & + \beta_7 Mowing_{Mij} + \beta_8 Mowing_{Lij} \\ & + \beta_9 Chemical_{Mij} + \beta_{10} Chemical_{Lij} \\ & + \beta_{11} Price_{ij} \qquad [3] \end{aligned}$$

where *ASC* is the alternative specific constant for the purchase of new turfgrass; $ASC = 1$ if no purchase of new turfgrass is selected or -1 otherwise because effects coding was used during this study. Price refers to the average price of sod ($/ft^2). *Winterkill_M* and *Winterkill_L* are dummy variables representing medium (20%) and low (0%) levels of the area of lawn lost to winterkill; *Winterkill_M* = 1 if the level is medium or 0 otherwise, and *Winterkill_L* = 1 if the level is low or 0 otherwise. Shade is also a dummy variable representing shade-tolerant sod. *Shade* = 1 for shade tolerance or -1 otherwise. *Water_M* and *Water_L* are dummy variables representing medium (3000 gallons) and low (2000 gallons) watering requirements (per month); *Water_M* = 1 if the level is medium or 0 otherwise, and *Water_L* = 1 if the level is low or 0 otherwise. *Mowing_M* and *Mowing_L* refer to the change in mowing cost, where *Mowing_M* = 1 if the level is no change or 0 otherwise, and *Mowing_L* = 1 if the level is low (20% less) or 0 otherwise. *Chemical_M* and *Chemical_L* represent the change in the costs of fertilizer, pesticide, and herbicide. *Chemical_M* = 1 if the level is no change or 0 otherwise, and *Chemical_L* = 1 if the level is low (20% less) or 0 otherwise. Although pesticide is a comprehensive term encompassing herbicides, the distinction between these two terms is made to prevent confusion and enhance clarity for survey participants. This separation is intended to ensure that respondents fully comprehend the nature of the inquiry. We posit that by avoiding ambiguity regarding whether pest control pertains to both weeds and insects, respondents are more likely to provide accurate and informed responses. The base level of each attribute is dropped to avoid perfect collinearity, and the attributes are *Winterkill_high* (40%), *Shade_no* (no shade tolerance), *Water_high* (4000 gallons/month), *Mowing_high* (20% more), and *Chemical_high* (20% more). Table 1 provides a summary of attributes and the levels of each attribute used in the choice experiment.

Preference shares. The mixed logit model is estimated using effects-coded data because effects coding allows us to recover the WTP for each attribute's base level, which makes it possible to compare consumer preferences across attributes rather than according to the attribute level. The base-level WTP can be recovered by taking the negative sum of coefficients of other levels of the attribute. After recovering the base-level WTP for each attribute, we calculated the preference share of each attribute in accordance with the work Wolf and Tonsor (2013) and Ghimire et al. (2016). These preference shares can show shifts in cardinal rankings for each attribute before and after the outbreak of COVID-19. We derived percentages reflecting the relative importance of each attribute based on consumer preference to ensure that the sum of shares for the five attributes equaled 100%. The preference share for each attribute is calculated as follows:

$$PS_k = \frac{\widehat{RN}_k}{\sum_{k=1}^{5} \widehat{RN}_k} \quad [4]$$

where PS_k is the share of preference of the k^{th} attribute and $\widehat{RN}_k$ is the range of WTP estimates for the k^{th} attribute.

Panel data model. Demographic factors such as age, income, sex, and education have been known to affect consumer purchasing decisions and their WTP (Ali and Ali 2020; Bonny et al. 2017). To estimate the effect of demographic and risk attitude variables on participant's WTP before and after the pandemic, a panel data model was considered during this study. The panel estimation is preferred to a single cross-section or pooled data regression because of its ability to control problems of unobserved heterogeneity and omitted variable bias (Campbell 2007; Hsiao 2007). During our panel data estimation, the dependent variable is the individual specific WTP estimate obtained from Eq. [1] for each attribute level, and the regressors are dummy variables representing age, annual income level, education level, risk attitude, and other demographic characteristics that describe the respondent. The dependent variable is generated by pooling the WTP of each level of attribute because the panel estimation is conducted for each attribute. Then, the model is specified as follows:

$$WTP_{in} = \alpha_i + \boldsymbol{X}_{in}\beta + \varepsilon_{in} \quad [5]$$

where subscripts i and n represent respondent and attribute levels, respectively, α_i is the intercept term that varies by each individual i, and $\boldsymbol{\beta}$ is a vector of parameters for the demographic variables $\boldsymbol{X}_{in}$. Our demographic variables include sex (male and female), annual income (categorized as <\$50,000, \$50,000–\$100,000, and >\$100,000), education (high school diploma and bachelor's degree or higher), and risk attitude (risk averse or risk seeking). Following the Census Bureau's classification of geographic regions (US Census Bureau 2017), our respondents' state of residence is classified into two regions: the South Atlantic and South-Central regions. Two surveys, one before COVID-19 and the other for after COVID-19, were conducted in 11 southern states because our study estimated consumer preferences for warm-season grasses. The South Atlantic region comprises Florida, Georgia, North Carolina, and South Carolina, whereas the South-Central region includes Alabama, Arkansas, Louisiana, Missouri, Oklahoma, Tennessee, and Texas. Other attributes that were measured include age (categorized as younger than 50 years and 50 years older), race (white and nonwhite), and location (urban and rural); the random error term, ε_{in}, represents a standard measurement error. A random effect model was used during this study because it allows for the inclusion of panel invariant variables. Note that all explanatory variables (for example, demographic characteristics) are panel invariant variables in our model.

Survey design and data. We conducted two online surveys of homeowners residing in 11 southern states in the United States, and both surveys were administered by the Qualtrics online survey platform (Qualtrics 2019, 2021). Qualtrics was hired to draw the sample frame from their proprietary panel. The first survey was conducted in Jan 2019, 1 year before the first COVID-19 case was reported in the United States, and the second survey was conducted in Apr 2021, when people were fully experiencing pandemic effects. Respondents to the first and second surveys totaled 1124 and 1252, respectively, after filtering out individuals who were younger than 18 years, did not live in the targeted states, or completed the survey within less than 1 min. Each respondent had nine choice sets, and each choice set included three alternatives. In our choice experiment, each respondent had a different choice set question with respect to the level of attributes and sod price. The attributes considered were winterkill, water requirement, shade tolerance, mowing costs, chemical costs, and sod price. In this article, we use the terms "water requirement" and "drought tolerance" interchangeably. Specifically, the level of water requirement served as a metric for assessing the amount of water that turfgrasses require for optimal growth, with those needing less water considered as drought-tolerant. Additionally, the terms "winterkill-resistant" and "stress-resistant" are also used interchangeably. In this context, "winterkill-resistant" reflects the ability of turfgrasses to endure stress from cold weather conditions. With a full factorial design of 512 ($2 \times 4^3 \times 4$) consisting of attributes at various levels, we used a fractional factorial design comprising 18 choice sets that were divided into two blocks, and each block consisted of nine choice sets with three alternatives. Alternatives A and B represented a combination of levels of attributes and sod prices, whereas alternative C was a no-purchase selection or status quo. An example of choice set questions used in the two surveys is presented in Fig. 1.

In addition to the choice set questions, respondents were also queried about their age, sex, educational background, housing type, risk perception, and other relevant demographic information. To elicit consumers' risk perception during both surveys, respondents were asked the following question: "How concerned are you about an extreme weather caused by climate change?" A Likert scale of 1 to 10 was used to score the answers, with 1 representing "not concerned" and 10 representing "very concerned." Researchers have used similar methods to assess how people perceive climate risks by gathering responses from climate perception responses using Likert scales (Tam and McDaniels 2013). In the field of behavioral research, perception sometimes serves as a tool for gauging climate risks (Ullah et al. 2015). Based on the individuals' responses, all individuals with a score of 1 to 4 were classified as risk-seeking, whereas those with a score of 7 to 10 were classified as risk-averse. Individuals with a score of 5 or 6 were not included to establish two distinctive risk-attitude groups.

Results and Discussion

Estimates of mixed logit model. Estimates of the mixed logit model for the periods before and after the COVID-19 pandemic are presented in Table 2. All WTP estimates indicated that consumers preferred improved turfgrasses with reduced levels of low-input and stress-resistant attributes, and most estimates were statistically significant, at least at the 10% level. By comparing the WTP before and after COVID-19, we found that, overall, consumers' WTP increased during the COVID-19 pandemic period for attributes except for Winterkill_M, Winterkill_L, Mowing_M, and Chemical_M, and that the WTP differences were statistically

Table 1. Attributes and levels of attributes used in the choice experiment.

Attribute	Levels
Average price (\$/ft^2)	0.1, 0.2, 0.3, 0.4
Winterkill	L (0), M (20), H (40)
Shade tolerance	Yes or no
Water requirement	L (2000), M (3000), H (4000)
Mowing cost	L (20% less), M (no change), H (20% more)
Chemical cost	L (20% less), M (no change), H (20% more)

H = high level; L = low level; M = medium level.

Choice set: Option A and B represent two different sets of sod/turfgrass characteristics. Which option (A, B, or C) would you be most likely to purchase?

Attributes	Option A	Option B	Option C
Area of lawn lost to winter kill	40%	20%	If A or B were the only available options, I would not purchase new sod for my lawn
Shade tolerant sod	No	Yes	
Watering requirement (gallons/month)	Medium (3000 gallons/month)	High (4000 gallons/month)	
Mowing cost	20% less than now	20% more than now	
Fertilizer, Pesticide, and Herbicide (weed killer) cost	No change	20% more than now	
Average purchase price of sod ($/ft^2)	$0.10	$0.30	
I would choose	☐ A	☐ B	☐ C

Fig. 1. Example of a choice set question soliciting consumer preferences and willingness to pay.

significant only for ASC, Winterkill_M, and Water_L.

The negative coefficients of ASC indicated that consumers preferred turfgrasses with enhanced traits to the turfgrasses currently available. After COVID-19, the estimate of the ASC parameter became substantially larger than that during the period before COVID-19, and the difference was statistically significant at the 1% level. The findings clearly indicated that the overall value of enhanced turfgrasses, particularly low-input cultivars such as water-conserving and low-maintenance turfgrasses, has increased after the pandemic compared with the levels before the pandemic.

Before the pandemic, homeowners' marginal WTP for medium and low levels of winterkill-tolerant turfgrass were an additional $0.055 and $0.128, respectively, compared with the high level (40%) of winterkill. However, following the outbreak of COVID-19, the WTP decreased to $0.026 and $0.115 for medium and low levels of winterkill-tolerant turfgrass, respectively, and the difference was statistically significant at the 10% level only for the medium level winterkill. This preference change could be attributed to the exceptional winter conditions experienced in 2019, which included rare snowfall, destructive tornados, and a record-breaking bomb cyclone impacting various states, such as Louisiana, Tennessee, Missouri, Arkansas, Texas, and Kansas. These severe storms brought about tornadoes, extreme flooding (e.g., Storm Diego and Storm Fisher), as well as substantial snow, sleet, and ice (Smith 2020; The Weather Channel 2018). Considering that the winter storm of 2019 had a more prolonged and adverse impact on the southern states compared with that of 2021, and considering that the prepandemic survey was conducted in Jan 2019, in the middle of a harsh winter, consumers could have been more concerned and willing to pay a higher price for winterkill-resistant turfgrass in 2019 than in 2021, irrespective of the pandemic. Estimates of WTP for shade-tolerant sod increased from $0.113 to $0.134 after the COVID-19 outbreak compared with those for nonshade-tolerant sod. However, the difference was not statistically significant at the 10% level. The WTP for turfgrasses with both medium and low water requirements (compared with that with a high water requirement) increased during the pandemic, although the difference between low and high water requirements was only statistically significant at the 5% level. Medium mowing and medium chemical requirements were statistically significant, at least at the 5% level, during the period before COVID-19, but they were not statistically significant after the outbreak of COVID-19. Coefficients of low mowing and chemical spray costs were statistically significant, at least at the 5% level, for the periods before and after the pandemic, indicating that turfgrasses with low mowing and chemical costs were preferred to those with high mowing and chemical costs.

WTP according to the risk attitude group. The mixed logit model was re-estimated by the risk attitude groups to determine whether results reported in Table 2 were different according to consumers' risk attitudes. As stated, individuals were assigned to risk-seeking and risk-averse groups when the scores of their responses to a climate change question were 1 to 4 and 7 to 10, respectively, using a Likert scale from 1 (not concerned) to 10 (very concerned). The WTP estimates for each group are presented in Table 3. Consistent with our findings provided in Table 2, consumers' WTP increased during the pandemic period in most cases. It was also noted that WTP of risk-averse consumers were mostly higher than those of risk-seeking consumers during both time periods, and increased WTP of the risk-averse group during the aftermath of COVID-19 were larger than those of the risk-seeker group. Our results suggest that consumer demands for the improved attributes are likely to increase with natural disasters and outbreaks of infectious diseases regardless of consumers' risk attitudes, and the increased demand would be more significant among risk-averse consumers than among risk-seeking consumers.

Estimates of ASC clearly showed that homeowners' preferences for improved cultivars significantly increased after the outbreak of COVID-19, and that the increase in WTP of risk-averse consumers was greater than the increase in the WTP of risk-seeking consumers both before and after the outbreak of COVID-19. Similar outcomes are observed for Water_M, Water_L, Mowing_L, and Chemical_L. However, estimates of Winterkill_M were statistically significant only for the period before the pandemic without showing any impact of the COVID-19, possibly because of the exceptionally harsh winter conditions experienced in 2019. Overall, COVID-19 increased consumers' WTP for improved turfgrass attributes; except for Mowing_M and Chemical _M, risk-averse individuals reacted to COVID-19 more strongly than risk-seeking individuals. The observed outcome can be ascribed to an increase in the number of risk-averse individuals following the onset of

Table 2. Mixed logit model estimates of turfgrass attributes before and after COVID-19.

	Willingness to pay estimates		
Attributes	Before COVID-19	After COVID-19	Difference
ASC	−0.577*** (0.031)	−0.927*** (0.068)	−0.35***
Winterkill_M (20% loss vs. 40% loss)	0.055*** (0.009)	0.026* (0.014)	−0.029*
Winterkill_L (0% loss vs. 40% loss)	0.128*** (0.013)	0.115*** (0.020)	−0.013
Shade (Yes vs. no)	0.113*** (0.010)	0.134*** (0.017)	0.021
Water_M (3000 gallons vs. 4000 gallons)	0.042*** (0.008)	0.059*** (0.013)	0.017
Water_L (2000 gallons vs. 4000 gallons)	0.161*** (0.015)	0.225*** (0.024)	0.064**
Mowing_M (0% change vs. 20% more)	0.034*** (0.10)	0.007 (0.016)	−0.027
Mowing_L (20% less vs. 20% more)	0.040*** (0.009)	0.054*** (0.014)	0.014
Chemical_M (0% change vs. 20% more)	0.026** (0.009)	0.010 (0.016)	−0.016
Chemical_L (20% less vs. 20% more)	0.018** (0.009)	0.039** (0.014)	0.021
N	10,116	11,268	

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
*SE*s are in parentheses.

Table 3. Comparative willingness to pay estimates of turfgrass attributes before and after COVID-19 by risk behavior.

Attribute	Risk-seeking			Risk-averse		
	Before COVID-19	After COVID-19	Difference	Before COVID-19	After COVID-19	Difference
ASC	−0.233***	−0.579***	−0.346***	−0.766***	−1.402***	−0.636***
	(0.019)	(0.077)		(0.056)	(0.177)	
Winterkill_M	0.035**	0.024	−0.011	0.070***	0.007	−0.063**
(20% loss vs. 40% loss)	(0.013)	(0.015)		(0.013)	(0.026)	
Winterkill_L	0.122***	0.135***	0.013	0.138***	0.153***	0.015
(0% loss vs. 40% loss)	(0.019)	(0.021)		(0.019)	(0.039)	
Shade	0.117***	0.117***	0	0.111***	0.149***	0.038
(Yes vs. no)	(0.014)	(0.029)		(0.015)	(0.032)	
Water_M	0.035**	0.040**	0.005	0.053***	0.084***	0.031
(3000 gallons vs. 4000 gallons)	(0.011)	(0.015)		(0.012)	(0.025)	
Water_L	0.155***	0.164***	0.009	0.175***	0.308***	0.133**
(2000 gallons vs. 4000 gallons)	(0.019)	(0.028)		(0.023)	(0.049)	
Mowing_M	0.042***	0.005	−0.037	0.031**	−0.001	−0.032
(0% change vs. 20% more)	(0.013)	(0.019)		(0.015)	(0.029)	
Mowing_L	0.042***	0.054**	0.012	0.050***	0.076**	0.026
(20% less vs. 20% more)	(0.012)	(0.017)		(0.014)	(0.026)	
Chemical_M	0.030**	0.014	−0.016	0.014	0.001	−0.013
(0% change vs. 20% more)	(0.013)	(0.023)		(0.013)	(0.028)	
Chemical_L	0.023*	0.032	0.009	0.027**	0.059**	0.032
(20% less vs. 20% more)	(0.013)	(0.024)		(0.013)	(0.025)	
N	2062	1556		5300	4924	

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
*SE*s are in parentheses.

the COVID-19 pandemic. Before the pandemic, the percentage of risk-averse individuals was 49%, but this proportion escalated to 54% in the aftermath of the COVID-19 outbreak. The results of statistical tests indicated that the disparities in the WTP before and after COVID-19 were statistically significant for estimates related to ASC, Winterkill_M, and Water_L, and reached significance, at least at the 5% level.

Preference rankings of turfgrass attributes. To determine preference rankings among the selected turfgrass attributes, preference shares were computed using Eq. [4]. This analysis permitted cross-attribute comparisons and offered insights into potential shifts in consumer rankings of the attributes after the pandemic. The estimated rankings can reveal the evolving priorities of respondents' preferences in the wake of the pandemic, aiding turfgrass industry stakeholders in adapting to the changing landscape. Consumers' preference rankings for turfgrass attributes considered during this study were mostly unaltered after the COVID-19 pandemic (Table 4). Specifically, the order of rankings was as follows before COVID-19: water requirement, winterkill, mowing costs, shade tolerance, and chemical costs; however, the order changed only slightly to the following after the pandemic: water requirement, winterkill, shade tolerance, mowing costs, and chemical costs. A further analysis found that the preference rankings according to the risk attitude group did not significantly change. This result aligned with findings of other researchers, such as Knuth et al. (2023), who found that homeowners have a higher WTP for turfgrass options with low-input attributes, and Ge et al. (2020), who identified drought tolerance as the highest-ranking turfgrass attribute during their analysis. This study also found growing popularity and demand for shade-tolerant turfgrass because nonshade tolerance has been recognized as detrimental to turfgrass quality, especially in southern areas with abundant trees and shrubs (Chhetri et al. 2019; Trappe et al. 2011).

Impact of demographic characteristics and risk attitudes on WTP. One important step to understand target markets for improved turfgrasses might be to examine the relationship between individuals' demographic and risk attitude characteristics and their WTP for the enhanced turfgrass attributes. An analysis of potential changes in this relationship after COVID-19 could provide pertinent information about how the target markets would be formed under future climate changes and natural disasters.

Table 5 shows the results of the panel data model from Eq. [5] during the periods before and after COVID-19. The model was estimated at the attribute level by pooling the WTP from the mixed logit model, which was estimated at each level of attributes (Table 2). The panel estimation was conducted using data from respondents who exhibited positive preferences for the enhanced turfgrass attributes. Table 5 also presents estimates from a pooled sample encompassing all attributes. The results showed that consumers' demographic characteristics were not major factors that affected change in the WTP, except age and risk attitude. People who are 50 years or older had higher WTP for all attributes, and the estimates were statistically significant, at least at the 5% level, except for mowing (for both periods) and chemicals (for the period after COVID). People who are risk-averse had higher WTP than risk-seekers overall, and estimates of risk-averse respondents were statistically significant for all attributes, water, and winterkill samples, at least at the 5% level of significance. The estimates were also greater during the pandemic period than those estimated before COVID-19, which is consistent with our findings presented in Table 3. All other demographic variables such as sex, income, region, and location were not statistically significant at the 10% level. Our results indicated that consumers' age and risk attitudes were key factors that affected change in individuals' WTP for improved turfgrass attributes, and that after the global pandemic, consumers' risk attitudes became even more important for determining consumers' WTP, particularly for water conservation and winterkill-resistance.

Table 4. Preference share ranking of turfgrass attributes before and after COVID-19.

Attribute	Before COVID-19	After COVID-19
Winterkill	32.26% (second)	23.23% (second)
Shade tolerance	11.72% (fourth)	12.16% (third)
Water requirement	37.76% (first)	46.19% (first)
Mowing costs	11.82% (third)	10.44% (fourth)
Chemical costs	6.43% (fifth)	7.99% (fifth)

The preference rankings are in parentheses, with the first being the most preferred and the fifth being the least preferred.

Conclusions

Based on our empirical findings, we observed two important implications that can elucidate the future development of improved turfgrass cultivars. First, many studies in the climate change literature predicted more rapid climate changes in the future, including warmer temperatures, drought, higher sea levels, and more severe changes in weather patterns.

Table 5. Panel data model estimates for demographic variables and risk attitude before and after COVID-19.

	All attributes		Water		Winterkill		Mowing		Chemical		Shade	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Age (younger than 50 years)	−0.012***	−0.015***	−0.019***	−0.031***	−0.018***	−0.021**	−0.001	−0.000	−0.002**	−0.001	−0.025***	−0.024***
	(0.002)	(0.003)	(0.005)	(0.008)	(0.005)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)
Female	0.001	0.003	−0.001	0.018**	0.002	−0.007	−0.000	−0.000	0.001	0.001	0.010	−0.005
	(0.002)	(0.003)	(0.005)	(0.008)	(0.005)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)
Income ($50k–$100k)	0.003	0.003	0.008	0.002	−0.002	0.012	−0.001	0.000	−0.000	−0.000	0.013	0.001
	(0.003)	(0.004)	(0.007)	(0.010)	(0.006)	(0.010)	(0.001)	(0.001)	(0.001)	(0.002)	(0.008)	(0.009)
Income (>$100k)	0.003	0.006**	0.004	0.014	0.002	0.013	−0.001	−0.001	−0.001	0.000	0.014*	0.004
	(0.002)	(0.003)	(0.006)	(0.010)	(0.006)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.009)
Undergraduate	0.003	0.005*	−0.007	0.010	0.007	0.006	−0.001	−0.000	0.001	−0.002	0.007	0.007
	(0.002)	(0.003)	(0.006)	(0.008)	(0.005)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)
Risk-averse	0.008***	0.014***	0.020***	0.037***	0.011**	0.020**	−0.000	0.000	−0.000	0.001	−0.001	0.000
	(0.002)	(0.003)	(0.005)	(0.008)	(0.005)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.006)
Region	0.002	0.000	0.006	0.001	−0.001	0.002	−0.000	0.000	−0.001	−0.001	0.008	−0.002
	(0.002)	(0.003)	(0.005)	(0.008)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.007)
Race	−0.002	0.001	−0.004	0.000	−0.010*	−0.003	−0.001	0.000	0.000	−0.002	0.009	0.009
	(0.002)	(0.003)	(0.005)	(0.008)	(0.005)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)
Urban	−0.001	−0.003	−0.010	−0.009	0.002	0.001	0.001	−0.000	0.002	0.002	0.008	−0.002
	(0.002)	(0.003)	(0.006)	(0.008)	(0.006)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)
Constant	0.077***	0.080***	0.113***	0.110***	0.114	0.128***	0.041***	0.033***	0.026***	0.034***	0.120***	0.166***
	(0.004)	(0.006)	(0.010)	(0.018)	(0.009)	(0.017)	(0.002)	(0.001)	(0.002)	(0.003)	(0.012)	(0.017)
σ_ε^2	0.087	0.114	0.129	0.187	0.115	0.159	0.016	0.018	0.021	0.020		
N	7362	8867	1636	1926	1636	1926	1636	1926	1636	1926	818	963

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

*SE*s are in parentheses.

Before = before COVID-19; After = after COVID-19.

Epidemiologists claimed that climate change is likely to worsen outbreaks of various infectious diseases. Our results implied that the demand for drought-tolerant and stress-resistant turfgrasses would continuously increase under the environments with rapid climate change. Second, our study found that the increased demand for drought-tolerant and stress-resistant turfgrasses by risk-averse individuals was greater than that of other groups under global disasters, such as COVID-19. This study also observed that the risk-averse group expanded under the COVID-19 environment. These findings suggested that future climate changes may lead to an increased demand for drought-tolerant and stress-resistant turfgrasses, especially by risk-averse consumers and adults 50 years and older. This is likely to occur under various scenarios of future climate changes and natural disasters.

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