An empirical estimate of the value of manageable soil quality

Michael Black and Richard T. Woodward
mblack438@gmail.com & r-woodward@tamu.edu

Selected Paper prepared for presentation at the 2021 Agricultural & Applied Economics Association Annual Meeting, Austin, TX, August 1 - August 3

Work in Progress - Do Not Cite

An empirical estimate of the value of manageable soil quality

Michael Black* Richard T. Woodward†

Abstract

The on-farm value of manageable soil quality characteristics has long been estimated using the value of agricultural production. Farmers may, however, value soil quality beyond its production potential. We construct a pivoted discrete choice experiment (DCE) for farmers in a central Texas watershed to elicit the value of manageable soil quality characteristics. We engage with focus groups and interdisciplinary scientists to create a survey instrument that is both statistically state-of-the-art and realistic for farmers with experience managing soil. We find that farmers are willing to pay for improvements in manageable soil quality characteristics, with some evidence of preference heterogeneity. Our empirical estimates are novel and should be validated through further study.

Keywords: soil, non-market valuation, land, discrete choice experiments
JEL Codes: Q24; Q51; C25

*U.S. Food and Drug Administration
†Department of Agricultural Economics, Texas A&M University

1 Introduction

During the past century, the United States has addressed soil conservation through a variety of conservation acts and services.[1] Today, the United States Department of Agriculture (USDA) spends approximately $6 billion each year on conservation programs.[2] Despite the evident importance of soil conservation, we have an incomplete picture of the value of soil quality improvements.

The benefits of soil quality improvements can accrue both on and off the farm, and recent literature has mostly focused on the off-farm benefits. It is widely recognized that soil provides a bevy of ecosystem services that are valuable to society, such as flood control, recreational benefits, and carbon storage (Dominati et al., 2014; Jonsson and Daviosdottir, 2016; Lal, 2014; Hansen and Hellerstein, 2007; Hansen and Ribaudo, 2008). Researchers have used a variety of non-market valuation tools to value the effect that soil conservation has on the provision of these ecosystem services.[3]

Meanwhile, estimation of the on-farm benefits of soil quality improvements is stuck in time. Early work on the on-farm economic value of soil quality focused on changes in crop revenue or return-on-investments associated with soil conservation efforts (Ciriacy-Wantrup, 1947). After the Soil and Water Resources Conservation Act of 1977, there was renewed interest in the value of soil conservation, though most work was anchored in theoretical optimal control models (Barbier, 1990; Barrett, 1991; McConnell, 1983; Burt, 1981). A seminal paper on the optimal control of soil resources from McConnell (1983) assumes that a farmer seeks to maximize net revenues for her operation by considering the depth of soil as the only state variable. The economic literature on soil conservation since the 1980's has overwhelmingly focused on soil erosion Barbier (1990); Barrett (1991); Burt (1981); King and Sinden (1988); Lee (1980); Seitz and Swanson (1980), and benefits of soil conservation are typically captured in changes in revenues or input costs.

Estimating the on-farm benefits of soil quality improvements beyond erosion effects has received little attention. Nonetheless, farmers may value improvements in other characteristics like organic

[1]See, for example; Public Law 74-46 and the establishment of the Soil Conservation Service, Public Law 73-67 and the establishment of the Soil Erosion Service, the Flood Control Act of 1936, the Watershed Protection and Flood Control Act of 1954, and the Soil and Water Resources Conservation Act of 1977

[2]https://www.ers.usda.gov/topics/natural-resources-environment/conservation-programs/

[3]For an exhaustive summary of soil ecosystem service valuation studies, see Jonsson and Daviosdottir (2016).

matter and water infiltration. In this paper, we directly estimate the willingness-to-pay to improve a set of soil quality characteristics without translating the changes to revenue. We use a direct stated preference approach since revealed preference approaches are not appropriate in this setting. Revealed preferences for soil quality characteristics elicited through choices of conservation practices are confounded by unobservable factors such as inherent (non-manageable, e.g. depth of horizons, clay content, and soil order) soil characteristics, effort of the farmer, and farmer-specific cost considerations. Revealed preferences could be elicited from observing land purchases, but there is no widely available data on manageable soil quality. We therefore build a hypothetical scenario to identify farmer preferences for manageable soil quality characteristics. Specifically, we utilize a discrete choice experiment (DCE) which is a popular approach to valuing specific attributes of a resource (Hanley et al., 1998). We follow a well-established framework for constructing a DCE (Holmes et al., 2017), opting for a multinomial choice-sequence version, where respondents face greater than two alternatives from which to choose (multinomial), and make a choice multiple times (sequence) (Carson and Louviere, 2011). We ask respondents to choose between two land parcels to rent for their operation, where each land parcel has different levels of manageable soil quality and rental rates, and a status-quo option where they may choose neither parcel.

The United States Natural Resources Conservation Service (NRCS) provides technical and financial assistance to farmers to adopt soil conservation practices. To effectively balance the costs and benefits of soil conservation, farmers and agents need to understand the monetary value of soil quality improvement. For example, the official benefit-cost template for no-till conservation lists potential on-farm benefits such as "[i]ncreased infiltration", "high soil organic carbon", and "reduce[d]...potential for soil compaction".[4] Our estimates of the willingness-to-pay for improvements in these characteristics is the first step in monetizing these benefits, which helps the USDA make more informed choices.

This work focuses only on estimating the perceived benefits of improved soil health. To be fully policy-relevant, our estimates should be compared to the costs of achieving soil quality improvements across different types of farmers to better understand which farmers need the most or least incentive to adopt soil conservation practices. Our work can ultimately lead to more efficient funding and

[4] https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/technical/econ/data/?cid=nrcseprd1298864

targeting of conservation practices for the NRCS and similar agencies.

2 Survey Development

2.1 Study Area

The selected study area is the watershed of the Brazos River in central Texas. We are particularly interested in the middle portion of the basin, where farms share similar geological and climatic characteristics. The watershed consists of a few major land resource areas (MLRAs), as defined by the United States Department of Agriculture, Natural Resource Conservation Service (?). The major MLRAs in the region are the Texas Blackland Prairie and Texas Claypan areas. In both MLRAs, most soils are entisols, mollisols, and vertisols, and have an ustic soil moisture regime. Cropland and grassland are the dominant land covers and the major crops are cotton, corn, and sorghum. The average annual rainfall across both areas is 27 to 45 inches, and the average annual temperature is 64 to 70 degrees (?).

Ustic soil moisture regimes are soils that are intermittently dry and wet throughout the year (?). The soil moisture is generally adequate during the growing season but can be scarce during other times of the year. This differs from udic regimes, for example, which are consistently more moist throughout the year. Other MLRAs in Texas can be characterized by different soil orders and soil moisture regimes, for which management concerns (and therefore preferences for soil health characteristics) may vary significantly. We therefore target the Texas Blackland Prairie and Texas Claypan areas so that the difference in observed preferences is purely a function of manageable soil quality and not also a function of inherent geologic or climatic context for the farmer.

2.2 Attribute Selection

We adhere to standard best-practices laid out by Johnston et al. (2017) in design of the discrete choice experiment (DCE). For example, we use prior empirical results and pretesting to create a design that efficiently identifies key parameters[5]. When estimating preference parameters, previous

[5] See recommendation 4 in Johnston et al. (2017)

estimates can be used to create more efficient experimental designs. A common metric to measure is a design's *D-efficiency* (described in Appendix), which is a measure of how efficiently an experimental design can identify coefficients of interest. Given the number of choice sets and attributes for an experiment, a researcher can maximize the D-efficiency of the design (Rose and Bliemer, 2009) by selecting combinations of attribute levels. This section describes the design process that ensures both the choice occasion and the alternatives are realistic to avoid a long-standing concern of hypothetical bias (Murphy et al., 2005) and consequentiality (Groothuis et al., 2017).

In both characterizing the decision problem and defining the attributes of the choice alternatives, we sought early input from farmers in the study area. In June of 2018, we met with two groups of farmers: those who had adopted soil conservation practices, and those who had not. The groups were recruited with the help of local extension service agents, who identified the adopting status of each farmer. Each group was asked a similar set of questions. After reviewing the recorded transcripts of both group meetings, we found that water management, organic matter, yield, and biomass of crops were important measures of soil health (Bagnall et al., 2020).

After the focus groups, we constructed an initial DCE where farmers were asked to choose between parcels of land to rent, with different soil health attributes and price for each alternative parcel. The initial list of attributes was refined through conversations with soil scientists. For example, water retention is a measure of how much water is held in a given type of soil, but soil scientists cautioned that the water-holding capacity of a given soil is more likely a function of its inherent characteristics and is not manageable.[6] Other attributes, like previous yield, were dropped because of endogeneity concerns.

In designing a choice experiment, it is important to frame alternatives in a realistic way (Johnston et al., 2017). Soil health is measured in a variety of ways. Some popular soil science measures are bulk density (grams/cm^3), organic matter (% of soil sample), soil respiration (mg of CO_2/kg soil/time), and other technical measurements (Bünemann et al., 2018). However, simple non-technical measurements - like the number of earthworms in a clump of soil - can also be good indicators of soil health (Plaas et al., 2019). Walking the tightrope between meaningful technical measurements and measurements that have meaning to farmers led us to explore the concept of

[6]Personal communication with Dr. Dianna Bagnall and Dr. Cristine Morgan.

linking indicators, a term coined by Boyd et al. (2015). A linking indicator is one that indicates some important ecological measure, and also has meaning to the person interpreting it. For example, the hydraulic conductivity of soil (a measure of how fast water travels through soil) is sometimes referred to as K_{SAT}, and is measured in μm/seconds. If hydraulic conductivity is selected as an attribute in a choice experiment, should it be called "hydraulic conductivity", "K_{SAT}", "How fast water moves through the soil", or something else? Should it be measured in μm/seconds, or perhaps scaled to meters (or feet) per day?

The list of soil attributes were first identified using the focus groups and an initial review of the soil literature, and then refined after discussions with soil scientists and initial pre-tests of the survey with farmers. See Table 1 for the final list of attributes and levels. The four attributes used in the choice experiment are water infiltration, organic matter, compaction, and price. Water infiltration is a measure of how well water flows through the soil. The inherent characteristics of any soil (like sand and clay content) significantly influence water infiltration rates, but within a given soil class, variation in infiltration rates is likely due to soil management. We measure water infiltration as time (in hours) for an inch of standing water to absorb. Organic matter is the amount of organic material in a unit of soil, and we measure it in percentage terms. In pre-testing, farmers were familiar with measuring organic matter in percentage terms. Soil compaction is measure of how much resistance roots encounter when penetrating downwards. In certain conditions, pressure from heavy equipment can cause a compaction of the soil beneath the ground, which acts as a root barrier. The root barrier restricts the downward growth of the roots, causing plants to become less physically stable and produce less fruit as energy is re-routed to root exploration (Unger and Kaspar, 1994). The levels for all three soil attributes were set based on real in-field measurements taken at several field stations in the project area (Bagnall and Morgan, 2021).

The final attribute is the monetary vehicle. The choice occasion is the rental of a new field, so naturally the rental rate serves as the ideal monetary attribute.[7] Unfortunately, the average rental rates vary significantly over the study area. Figure 1 shows the average cash rental rate in USD from 2008 - 2020 for the State of Texas, with the Brazos River Watershed outlined in the first

[7]Some farmers in the focus group indicated their rental agreements are sometimes structured as crop-shares, but most were engaged in cash rentals.

Table 1: Discrete Choice Experiment Attributes and Levels

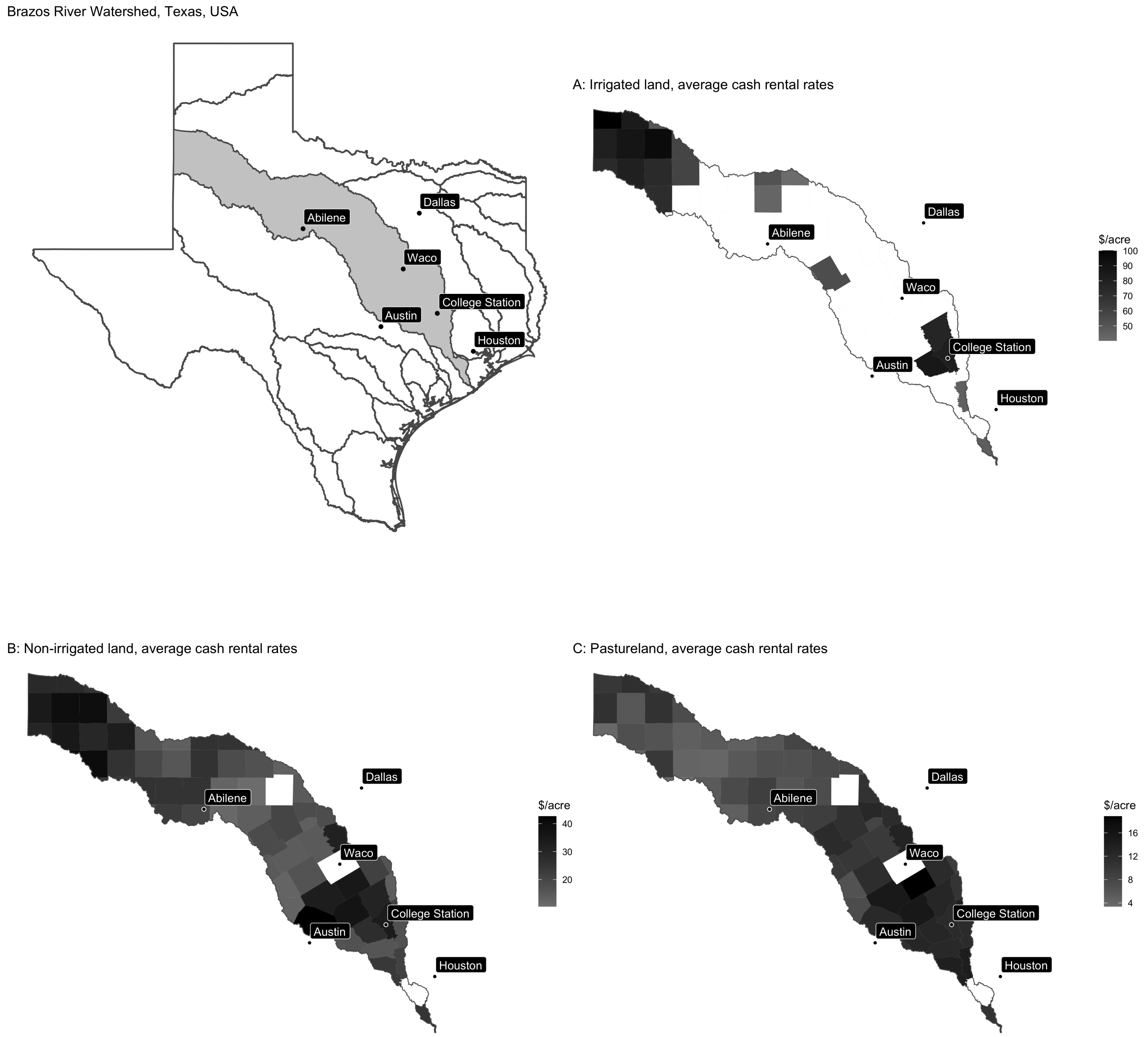
Attribute	Levels
Water infiltration	1 inch of standing water absorbed in 10 hours
	1 inch of standing water absorbed in 5 hours
	1 inch of standing water absorbed in 3 hours
Organic matter	0.5% by soil mass
	1% by soil mass
	2.5% by soil mass
Compaction	Does not restrict root growth
	Restricts root growth partially
	Restricts root growth substantially
Price	$10/acre less expensive that typical price
	Typical price
	$10/acre more expensive that typical price

Note: Soil attribute levels from Bagnall and Morgan (2021)

panel. There are significant differences across field types: irrigated land is generally more expensive than non-irrigated land, and pasture land is generally the cheapest of the three land types. Even within broad field types, there is substantial heterogeneity in typical cash rental rates across the study area. The large variance in land prices is problematic in determining the attribute levels. For example, a farmer operating on non-irrigated land near Austin (in the lower-middle region of the watershed) may be accustomed to rental rates of $40/acre. If we were to center the payment vehicle around $40 and present the survey to a farmer operating in an area where the average rental rates are closer to $10/acre, they may likely choose the opt-out alternative because the land is too expensive to rent.

To combat the large variance of the intended payment vehicle, we opt for a pivoted design, where the rental rates that each respondent is presented with are relative to their prior experience. Pivoted designs are relatively popular in the choice modeling literature (see Hensher and Rose (2007); Train and Wilson (2008); Hess and Rose (2009)). In a pivoted design, one attribute level is selected by the respondent based on some prior experience. The other attribute levels then *pivot* from the reference point, usually taking some symmetric deviation above and below the reference point. In our context, we ask the respondent to select his or her "base field." The base field is some field that the farmer knows well. If a farmer were to choose any of his/her fields, there may be substantial selection bias where the base field is under no-till, but also happens to be in a favorable location

Figure 1: Cash Rental Rates In Texas (Average, 2008 - 2020)



with favorable inherent soil characteristics. To minimize the potential selection bias, we ask farmers to select roughly the same type of field, regardless of tillage practice. If the field is under no-till or strip-till, we ask the respondent to select a field where the tillage is marginally effective. If the field is under conventional tillage, we ask the respondent to select a field where no-till/strip-till could be advantageous. Once the base field is selected, we ask a series of several questions to learn about the base field's size, location, crop mix, tillage practices, ownership structure, topography, and perceptions on urban encroachment and soil health. Finally, we ask each respondent for the typical cash rental rate for their base field. The respondent's typical rental rate is the reference point, and we add two additional levels: $10 above and $10 below the reference point.

2.3 Experimental Design

To our knowledge, we are the first to estimate the value of manageable soil characteristics using a discrete-choice experimental approach. Without prior expectations for any of the preference parameters, we initially construct a traditional factorial design using the R package *support.CEs*(Aizaki, 2012).[8] We then deployed the choice experiment and used the preliminary results to estimate preference parameters. These initial parameters were then used as priors, and we re-designed the choice experiment using the Stata package *dcreate*, which maximizes the D-efficiency of the experimental design assuming a conditional logit choice model (Hole, 2015).

In the initial design phase, we faced a design challenge. We avoided the following conditions which make little sense in real fields:

Avoidance Condition 1. Field A has higher water infiltration, equal or lower organic matter, and equal or higher compaction than Field B, or vice versa.

Avoidance Condition 2. Field A has lower water infiltration, equal or more organic matter, and equal or lower compaction than Field B, or vice versa.

While there are established methods to avoid certain attribute level combinations for a given alternative, there is little consideration in the literature for alternatives that are problematic only relative to otherwise unproblematic alternatives. There is no way to identify a problematic design until after the alternative combinations have been set. Our final design removes alternatives that *could* be problematic relative to others from the full-factorial combinations of all attributes and levels. For example, we removed alternatives that had the highest water infiltration rate, the lowest

[8] Specifically, we use a mix-and-match method described in Johnson et al. (2006): we find the orthogonal main-effects design (OMED), which is unique to our design of four attributes with three levels each. A new design is created by *rotating* the levels for each attribute up by one (and returning to the lowest for the highest attribute levels). The two designs represent two alternatives, with each row corresponding to a choice set. Next, each row is shuffled for both designs independently. Finally, a random draw is made from each design to construct the first choice set. The drawing continues with replacement until the number of drawable choice sets equals zero.

organic matter percentage, and the highest compaction level since this alternative would fail the first avoidance condition. We then iterate a full design until two conditions are met: 1) we avoid the identified problematic conditions and 2) we retain one choice occasion with a dominated alternative to check the monotonicity of preferences (Scarpa et al., 2007).

The final DCE is embedded in a larger survey consisting of 12 sections that address the research questions of the interdisciplinary team of economists, sociologists, and soil scientists. The first section collects general demographic information, the second collects information specific to the farmer's base field, the third collects perception of soil quality and effectiveness of soil conservation practices, the fourth is the choice experiment, and the remaining 8 sections are sociological in nature and use the theory of planned behavior (TPB) to understand why farmers make the decision to adopt or not adopt a practice.

3 Survey Results

The final survey was administered through the USDA National Agricultural Statistics Service (NASS) to guarantee a representative and random sample in our study area. A total of 575 usable responses were collected in 2020 from a total of 2,833 mailed surveys, for an effective response rate of 20.3%. See Table 2 and Figure 2 for selected summary statistics. Note that because of NASS confidentiality concerns, we cannot present median values or any other individually identifying statistic. The average respondent is 68 years old and has been in operation for approximately 34 years. The average respondent rents more acres (681) than he owns (479), which is consistent with our initial focus group conversations about the prevalence of renting land in central Texas. The average base field operation is approximately 77 acres, and for those who have adopted no-till on the field, they have almost 9 years of experience with no-till on average. Approximately 15% of the average base field is prone to flooding. Figure 2 summarizes categorical responses across a set of key questions. Almost half of respondents plan on continuing to operate in five years. A vast majority of respondents did not use strip-till in 2018, and had no plans to change. The same is true for no-till, though a more sizable 15% of the sample used no-till in 2018. Most respondents did not use outside crop consultants, and of those who did, the vast majority relied on the consultant's advice "somewhat" or "very little". The selected base field for respondents is, on average, rented, under conventional-till, and is gently sloping. Most respondents consider their base-field to be neither floodplain nor hilly/upland.

Table 2: Selected Summary Statistics, Farmer Survey

Survey Question	Mean	Std Deviation
Years in Operation	34.47	17.66
Age	68.30	12.02
Acres Owned	479.94	4,455.19
Acres Rented	681.25	2,700.69
Base Field Size (Acres)	77.03	174.08
Base Field Number of Years in No-till	8.91	35.77
Percent of Base Field Prone to Flooding	15.56	77.07

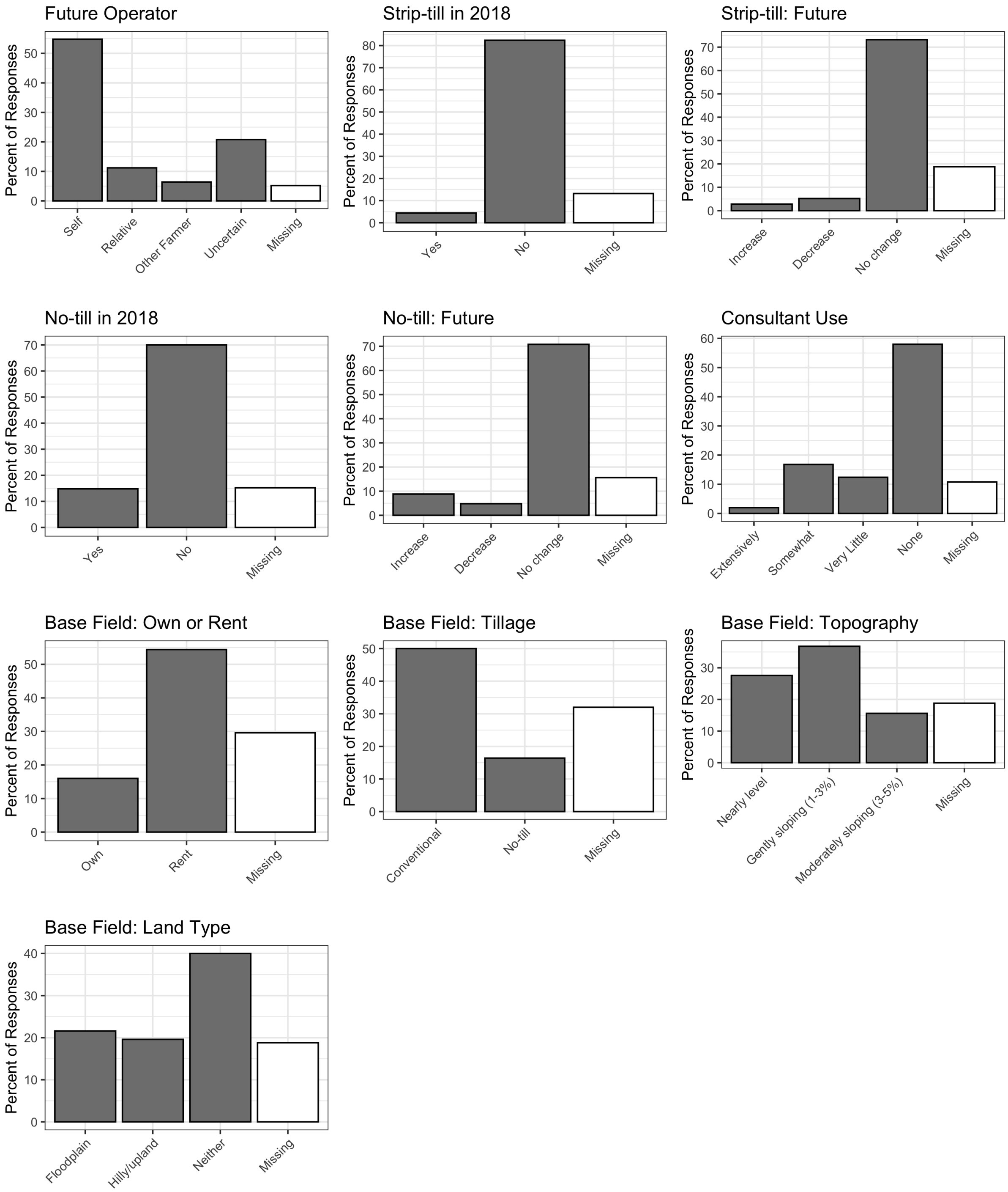
Note: Outliers cause large standard deviations. While outliers would normally be dropped, USDA NASS restrictions prevent the sharing of any data that could be used to identify a single operation. Outliers are therefore retained in our summary statistics.

4 Models

The statistical efficiency of the DCE design presupposes a conditional logit model of estimation (Hole, 2015). Our main modeling approach therefore characterizes respondent choice by using a random utility framework, estimated by a conditional logit (McFadden, 1974). The conditional logit setup ignores attribute preference heterogeneity across respondents. There is good reason to believe, however, that there may be substantial heterogeneity across respondent farmers. We try to capture preference heterogeneity in a variety of ways. First, we split the sample across base field rental rates, tillage practices, future operational plans, and base field topography. Second, we employ a latent class analysis to split the sample into distinct groups based on soil health attitudes. As we explain below, we identify four distinct groups of farmers based on these attitudinal questions. Third, we estimate several mixed logit regressions: one for every restricted sample in the conditional logit and latent class analyses.

In the next three subsections, we describe the model and estimation results for the standard conditional logit, latent class analysis, and mixed logit approaches.

Figure 2: Selected Summary Statistics, Farmer Survey



4.1 Conditional Logit Analysis

Following the standard random utility model, we assume that respondent i chooses alternative j at choice occasion t when the expected utility from choosing alternative j is the maximum of all possible alternatives k in the choice set J, i.e.:

$$U_{ijt} \geq U_{ikt}, \quad \forall k \in J \tag{1}$$

where utility is comprised of two separable components: a deterministic component V_{ijt} and a structural error ε_{ijt} assumed to exhibit a Type I extreme value distribution, i.e. $U_{ijt} = V_{ijt} + \varepsilon_{ijt}$. In our case, $J = \{\text{Field A, Field B, Neither Field A nor Field B}\}$. We model the probability that respondent i chooses alternative j at choice occasion t as:

$$P_i(j,t) = \frac{e^{V_{ijt}}}{\sum_{k \in J} e^{V_{ikt}}}, \tag{2}$$

where V_{ijt} is the deterministic portion of utility, and takes the form:

$$V_{ijt} = \alpha_j + X_{jt}\beta + \gamma r_{jt}. \tag{3}$$

The α_j term is a set of two dummy variables that indicate if alternative j is Field A or Field B. A negative α_j would suggest that respondents are less likely to choose one of the two main alternatives, and more likely to choose the opt-out alternative, *ceteris paribus*. The alternative-specific constants are not of particular interest in our study. The X_{jt} term is a matrix of values for the three selected soil attributes (water infiltration, organic matter, and compaction[9]) in the DCE. Finally, the r_{jt} term is the rental rate value for alternative j at occasion t. Recall that this is a pivoted variable, and thus takes one of three values: -1 if the rental rate is \$10 below the base rate, 0 if the rental rate is equal to the base rate, and 1 if the rental rate is \$10 above the base rate. The vector of estimated coefficients, β, and γ capture the marginal effect of a change in attribute levels on respondent utility.

Before estimating any model, we first filter out respondents that appear to not be making utility-maximizing decisions by eliminating respondents who choose a dominated alternative. We purposefully included a dominated alternative in choice occasion six to check for irrational choices. We also observe many respondents did not provide a base field rental rate, which is the center of the pivoted rental rate variable. While the pivoted design allows prior experience to enhance the realism

[9]Compaction is a categorical variable that takes three values: high, medium, and low. We set the reference level to be "low" and omit this category from estimation

in the choice experiment, the center pivot is not needed for estimation.[10] We retain respondents who did not provide the rental rate for their base field (approximately 19% of the sample) and assume the DCE was nonetheless realistic for this group.

See Table 3 for the conditional logit estimation results for each of the restricted samples described above. The base model which includes the entire sample is presented in column 1. All attributes significantly affect respondent utility, though there is a noticeable difference in magnitudes. We discuss relative magnitudes across attribute coefficients in the willingness-to-pay calculations below, where we scale the marginal change by a realistic change in soil management to more accurately compare differences in soil quality attribute preferences. The coefficients in Table 3 are most helpful when interpreting coefficient signs or comparing across models. Again focusing on the base model, the coefficients on water infiltration and organic matter are positive, which means as water infiltration or organic matter increase for a field, respondent utility associated with choosing that field increases. On the other hand, the coefficients on high and medium compaction are negative, which means that a field with high or medium compaction yields lower respondent utility – compared to a field with low compaction. Finally, the coefficient on rental rate is negative, suggesting that as the rental rate of a field increases, the respondent utility associated with choosing that field decreases.

After estimating the base model, we split the sample in a variety of ways. First, we create three rental rate groups: a *low-price group* with base field rental rates of \$0 - \$20 per acre, a *medium-price group* with base field rental rates of \$21 - \$40 per acre, and a *high-price group* with a base field rental rate of more than \$40 per acre. Second, we create a *conventional tillage group* who use conventional tillage on their base fields, and a *no-till/strip-till group* who use either no-till or strip-till on their base fields.[11] Third, we create three groups based on the planned operator in five years: *self* if the respondent plans on continuing to operate himself, *other* if the respondent plans on having a

[10] The coefficient and variable for the rental rate in equation 3 can be represented as: $\gamma(r_i + r_{jt})$ where r_i is the rental rate of the respondent's base field, and r_{jt} is the pivoted value, which can be the same as the base rate, or \$10 above or below that rate. Note that r_i can be factored out and as in all conditional logits, drops out of the estimation process because it varies only over individuals.

[11] We tried creating three tillage groups: conventional, no-till, and strip-till, but the number of strip-till users was too small for subsequent analysis. We therefore absorbed the strip-till group into the no-till group, recognizing that there may be important differences in soil preferences between no-till and strip-till producers. Unfortunately, we lack the power to identify any differences between the unconventional tillage groups.

relative or other person operating his fields, and *uncertain* if the respondent does not know who will be operating the farm in five years. Finally, we create two groups based on the topography of the base field: *level* if the base field is level (less than 1% slope), and *sloped* if the base field has any slope greater than 1%.

Columns 2 - 11 in Table 3 present the same conditional logit results for the restricted samples. Despite some noticeable differences in estimated coefficients across sample restrictions, all groups (sub-samples) yield somewhat similar results in coefficient magnitudes and identically-signed coefficients, all of which are significant at the 5% level. As we explore below, this leads to no significant differences in estimated willingness-to-pay across the groups. Note that all groups are not mutually exclusive; an individual in the medium rental rate group will also be in the level or sloped topography groups. However, within the group categories (rental rates, tillage practices, future plans, and topography), groups *are* mutually exclusive and a direct comparison of coefficient magnitudes can be made. For example, the high rental rate group is much less affected by changes in rental rates than the medium or low rental rate groups, as evidenced by the smaller coefficient on rental rate for the high rental rate group. Similarly, no-till/strip-till farmers appear to be much less sensitive to rental rates than conventional-till farmers in their choice to rent a field. At the same time, the no-till/strip-till farmers are more affected by all soil quality attributes than conventional-till farmers. Focusing on future plans, farmers who plan to continue to operate their own farms in five years are more affected by changes in water infiltration than farmers who are uncertain about their plans or are planning on selling their operation. Interestingly, there is little difference in the soil quality attribute coefficients for the two topography groups, though respondents with sloped base fields are more sensitive to rental rate changes than respondents on mostly level land.

Table 3: Conditional Logit Estimation Results

		Rental Rate Groups			Tillage Groups		Future Plan Groups			Topography Groups	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Base	Low Rental Rate	Medium Rental Rate	High Rental Rate	Conventional	No-till/Strip-till	Self	Other	Uncertain	Level	Slope
Rental Rate	−0.198***	−0.259***	−0.294***	−0.134***	−0.233***	−0.121**	−0.208***	−0.240***	−0.221***	−0.128***	−0.219***
	(0.029)	(0.057)	(0.063)	(0.057)	(0.038)	0.061)	(0.039)	(0.063)	(0.072)	(0.053)	(0.036)
Water Infiltration	4.311***	3.980***	5.493***	4.730***	4.319***	4.720***	4.736***	3.265***	3.497***	4.242***	4.255***
	(0.510)	(0.998)	(1.145)	(0.974)	(0.662)	(1.076)	(0.675)	(1.134)	(1.243)	(0.929)	(0.645)
Organic Matter	0.401***	0.421***	0.392***	0.343***	0.324***	0.603***	0.400***	0.337***	0.390***	0.429***	0.388***
	(0.042)	(0.080)	(0.088)	(0.080)	(0.053)	(0.091)	(0.054)	(0.089)	(0.104)	(0.077)	(0.052)
High Compaction[a]	−1.745***	−1.862***	−1.613***	−1.489***	−1.637***	−1.849***	−1.566***	−1.887***	−2.070***	−1.713***	−1.744***
	(0.109)	(0.217)	(0.219)	(0.206)	(0.134)	(0.257)	(0.142)	(0.230)	(0.272)	(0.204)	(0.135)
Medium Compaction[a]	−0.566***	−0.483***	−0.580***	−0.437***	−0.466***	−0.647***	−0.6105***	−0.458***	−0.573***	−0.608***	−0.512***
	(0.078)	(0.149)	(0.168)	(0.152)	(0.099)	(0.172)	(0.104)	(0.165)	(0.186)	(0.146)	(0.097)
Field A Intercept	0.186*	0.088	0.633***	−0.178	0.374***	−0.633***	−0.057	0.783***	0.570**	−0.124	0.305**
	(0.127)	(0.259)	(0.273)	(0.240)	(0.163)	(0.283)	(0.169)	(0.286)	(0.314)	(0.234)	(0.161)
Field B Intercept	0.073	0.305*	0.452**	−0.444**	0.161	−0.328*	−0.135	0.696***	0.307	−0.219	0.251**
	(0.111)	(0.216)	(0.239)	(0.215)	(0.143)	(0.237)	(0.148)	(0.242)	(0.267)	(0.205)	(0.139)
Observations	7,815	1,986	1,716	2,133	4,776	1,635	4,275	1,701	1,431	2,283	4,932
Log-Likelihood	−2,311.282	−5611.013	−471.865	−635.231	−1,399.470	−504.524	−1,310.564	−486.749	−401.685	−689.568	−1,453.835
AIC	4,636.564	1,236.026	957.730	1,284.462	2,812.940	1,023.047	2,635.127	987.498	817.370	1,393.137	2,921.67

Note: *p<0.1; **p<0.05; ***p<0.01

[a] *Omitted base category: low compaction*

4.2 Latent Class Analysis

As seen in Table 3, restricting the sample of respondents based on a single observable variable (like base field rental rate or tillage practice) results in relatively minor differences in coefficient estimates across groups. Splitting the sample does not remove potentially confounding opinion or behavioral patterns that can persist within restricted samples. For example, the *medium-price group* may have distinctly different groups of respondents, and estimating a single coefficient on various preference parameters hides potentially important heterogeneity.

Latent class analysis uses a set of categorical responses (referred to as *manifest* variables) to group respondents into distinct groups, or classes. The assigned class is referred to as the latent class, and is assumed to remove potential confounding between the set of manifest variables. Latent class models have been used, for example, to group agricultural producers based on their production decisions, the size of their operations, and their risk preferences (Chinedu et al., 2018). Latent class analysis (LCA) allows researchers to identify distinct groups of respondents that exhibit similar observed behavior, and an unobserved grouping variable is assumed to cause the observed patterns.

We hypothesize that farmers may be categorized into distinct groups based on their opinions on soil health and conservation practices. We in turn assume that the latent grouping variable causes differences in preferences for the discrete choice experiment and estimate a conditional logit for each latent class. Instead of a sample-wide fixed coefficient for each preference parameter, the LCA allows for a fixed coefficient for each class, which allows heterogeneous preferences across classes.

In setting up our latent class analysis, we use best practices outlined in Collins and Lanza (2009). The section preceding the DCE in the survey gathers information on the respondents' attitudes towards soil health. See Table 4 for a list of the fourteen questions and possible responses. For seven soil characteristics (water infiltration, organic matter, runoff, erosion, bulk density, compaction, and drainage), we as respondents 1) how important are changes in these characteristics to their base field, and 2) how no-till/strip-till would affect these characteristics on their base field.

We observe $J = 14$ manifest variables, each of which has $K = 6$ number of possible outcomes for each individual $i = 1, ..., N$. Let $Y_{ijk} = 1$ if respondent i responds with k for manifest variable j, and $Y_{ijk} = 0$ otherwise. Finally, let R be the number of anticipated latent classes, set prior to

Table 4: Latent Class Analysis Manifest Variables

Importance of a change in soil health characteristics to your base field:						
	Very Important	Fairly Important	Important	Slightly Important	Not Important	Don't Know
Increasing water infiltration	○	○	○	○	○	○
Increasing organic matter	○	○	○	○	○	○
Decreasing runoff	○	○	○	○	○	○
Decreasing erosion	○	○	○	○	○	○
Decreasing bulk density	○	○	○	○	○	○
Decreasing compaction	○	○	○	○	○	○
Increasing drainage	○	○	○	○	○	○
No-till or strip-till would increase or decrease soil characteristics on your base field:						
	Greatly Increase	Increase	Neither	Decrease	Greatly Decrease	Don't Know
Water infiltration	○	○	○	○	○	○
Organic matter	○	○	○	○	○	○
Runoff	○	○	○	○	○	○
Erosion	○	○	○	○	○	○
Bulk density	○	○	○	○	○	○
Compaction	○	○	○	○	○	○
Drainage	○	○	○	○	○	○

estimation. We return to the search for the optimal size of R below. Let π_{jrk} be the probability that an individual in class r responds with option k for manifest variable j. Finally, let p_r be the unconditional probability of any given individual belonging to class r. The probability density function of a vector of responses (Y_i) for individual i conditional on π and p is

$$Pr(Y_i|\pi, p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K} (\pi_{jrk})^{Y_{ijk}}, \tag{4}$$

and estimation proceeds by iteratively estimating $\hat{\pi}_{jrk}$ and $\hat{p}_r$, and replacing the initial expectations in the log-likelihood function version of equation 4 until the difference in log-likelihood between iterations becomes arbitrarily small. We estimate the above probabilities using the R package *poLCA* which identifies equation 4 using an expectation-maximization algorithm (Linzer et al., 2011; Bandeen-Roche et al., 1997).

The final step in searching for the optimal latent class analysis is to identify the number of classes R. We estimate the above latent class model for classes of size 1 to 5, and examine the model fit across the versions. We search for the log-likelihood closest to zero, and the model that minimizes the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Akaike, 1998; Schwarz et al., 1978). An LCA with class size $R = 4$ yields the overall best fit across the AIC and BIC statistics.

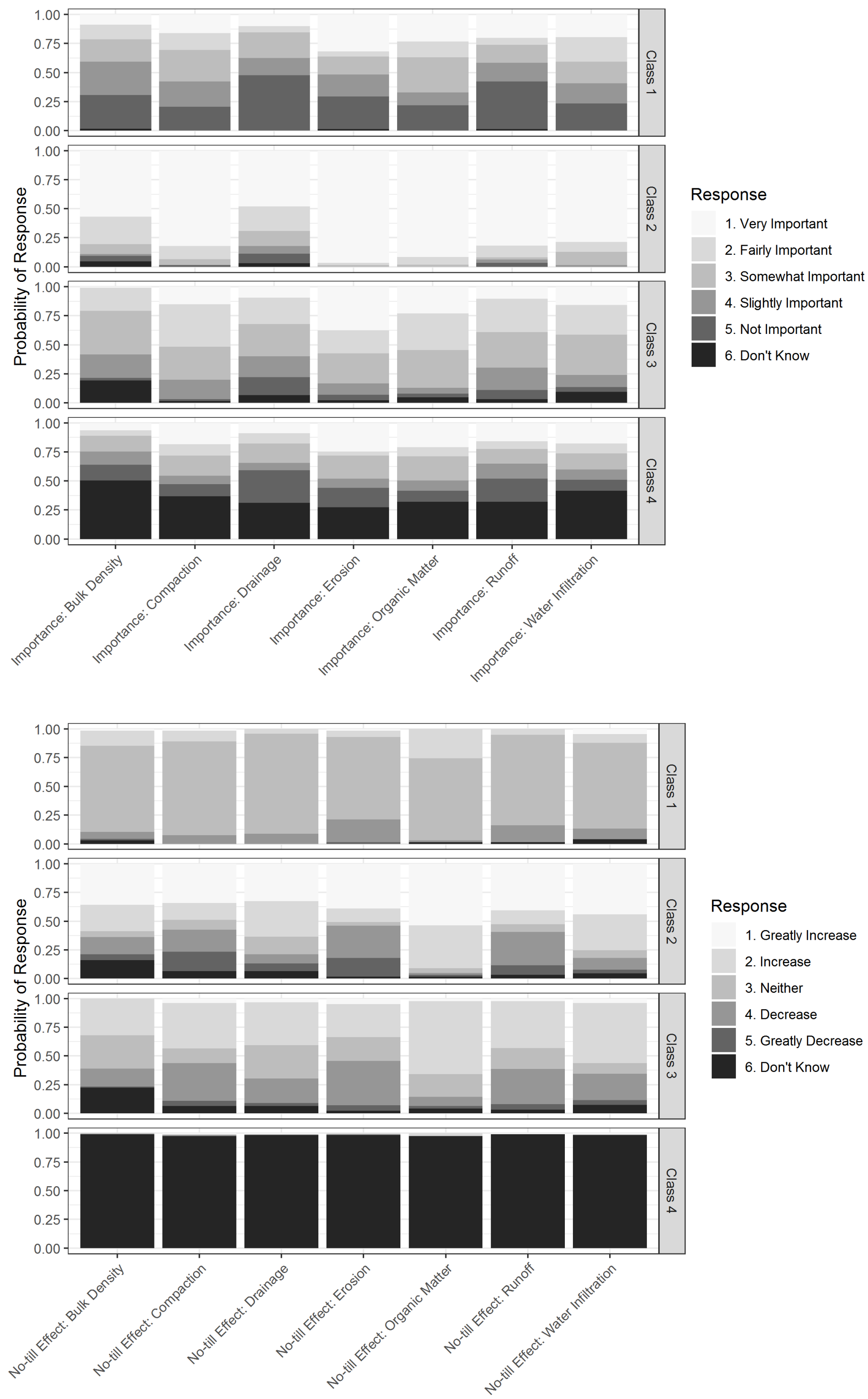
Figure 3 shows the class-conditional response probabilities from the LCA. There are clear patterns that allow us to name the generic latent classes for subsequent analysis. We focus first on the "importance" responses: how important are the soil health characteristics to respondents' base fields? Class 1 has varied predicted response probabilities, but members of this class are most likely to think the seven soil health characteristics are slightly or not at all important to their base field. Member of class 2 are overwhelmingly likely to think the characteristics are very important to their base field. The predicted response probabilities for class 3 are the most balanced, with no dominant response for any of the "importance" questions. Finally, members of class 4 are most likely to not know how important the soil characteristics are for the health of their base field.

Figure 3 also shows the class-conditional response probabilities for the "effect" responses: how do respondents think no-till/strip-till would affect the soil health characteristics? Members of class 1 are most likely to think no-till/strip-till would not change any of the characteristics. Members of class 2 are most likely to think no-till would *greatly* increase all characteristics. Members of class 3 are again balanced with roughly neutral opinions, except for water infiltration and organic matter, which members agree would increase under a no-till regime. Members of class 4 are almost certain to not know how no-till would affect the soil health characteristics.

Based on the predicted class-conditional response probabilities, we assign the following labels to the four generic classes. Class 1 is the *soil-apathetic* class, since members are likely to think the seven soil characteristics are not important and likely to think no-till would have no effect on the characteristics. Class 2 is the *soil-conscious* class, since members are likely to think the characteristics are very important and no-till would greatly increase them. Class 3 is the *moderate* class, for balanced and tepid predicted response probabilities. Finally, class 4 is the *uninformed* class, since members are likely to not know either the importance of the characteristics nor the effect no-till would have.

After forming the latent classes and assigning individuals to their respective classes, we estimate the standard conditional logit from the previous section for each latent class separately. Results are shown in Table 5. Across all four latent classes, the estimated coefficients are similar in sign and significance to each other and the general results from the conditional logit models of the last section. There are, however, some noticeable differences in magnitude across the latent classes. For example, the uninformed class has a much smaller coefficient on water infiltration than the other

Figure 3: Class-Conditional Response Probabilities, Latent Class Analysis



classes, and the coefficient on water infiltration is largest for the soil-conscious class. Similar to the conventional-till group from the previous section, the moderate class is most sensitive to rental rates. Despite these differences in coefficient magnitudes, the four classes yield estimates that are generally similar. This suggests – and we confirm below – that attitudes on soil health are not responsible for significant differences in willingness-to-pay for soil quality improvements.

Table 5: Conditional Logit Estimation Results By Latent Class

	(1) Soil-Apathetic Class	(2) Soil-Conscious Class	(3) Moderate Class	(4) Uninformed Class
Rental Rate	-0.201^{***}	-0.139^{**}	-0.247^{***}	-0.188^{***}
	(0.082)	(0.073)	(0.053)	(0.066)
Water Infiltration	6.427^{***}	5.799^{***}	5.168^{***}	2.361^{**}
	(1.382)	(1.311)	(0.930)	(1.161)
Organic Matter	0.323^{***}	0.527^{***}	0.369^{***}	0.455^{***}
	(0.113)	(0.113)	(0.075)	(0.092)
High Compaction[a]	-1.610^{***}	-1.963^{***}	-1.710^{***}	-1.554^{***}
	(0.298)	(0.288)	(0.191)	(0.248)
Medium Compaction[a]	-0.639^{***}	-0.787^{***}	-0.508^{***}	-0.402^{***}
	(0.212)	(0.209)	(0.140)	(0.178)
Field A Intercept	-0.560^{**}	0.045	0.258	0.140
	(0.347)	(0.315)	(0.227)	(0.300)
Field B Intercept	-0.580^{**}	-0.128	0.138	0.166
	(0.301)	(0.276)	(0.197)	(0.259)
Observations	1,062	1,296	2,460	1,398
Log-Likelihood	-319.992	-346.346	-703.812	-448.784
AIC	653.985	706.691	1,421.624	911.568

Note: *p<0.1; **p<0.05; ***p<0.01

[a] *Omitted base category: low compaction*

4.3 Mixed Logit Analysis

While splitting the sample for the conditional logit model by observable or latent characteristics may account for some important respondent heterogeneity, an alternative approach is to use a mixed logit model. In our mixed logit approach, we assume the indirect utility of respondent i selecting alternative j at choice occasion t to be:

$$V_{ijt} = \alpha_j + X'_{jt}\beta_i + \gamma W_{jt}, \tag{5}$$

which differs from equation 3 by allowing the vector of preference parameters on the soil quality characteristics, β, to vary over individuals. The mixed logit is an extension of the conditional logit (**?**), with the full form of utility still comprised of two parts: the deterministic indirect utility of equation 5 and a structural error that is still assumed to be distributed i.i.d. type I extreme value. The mixed logit is attractive because it allows for respondent preference heterogeneity and relaxes the restrictive IIA assumption required for the conditional logit (**?**). However, because β_i is a random variable, it takes some distribution, i.e. $f(\beta_i|\theta)$, and we make an assumption about the shape of that distribution. Specifically, we recover the parameters in equation 5 assuming a normal distribution of β_i for each soil quality characteristic and therefore recover the mean $\bar{\beta}$ and standard deviation σ of $f(\beta_i|\theta)$. We then explore the differences in estimated coefficients.

Recent advances in the mixed logit literature suggest that the typical distributional assumptions of $f(\beta_i|\theta)$ can result in unreliable WTP estimates, and more flexible semi-parametric distributional approaches (polynomials, splines, step-functions) can improve the reliability of WTP estimates (Bazzani et al., 2018; Train, 2016; **?**). Our empirical estimates for MWTP for improvements in manageable soil quality characteristics are, however, novel. We therefore do not have strong prior expectations that heterogeneous preferences exist, much less the shape of the distribution of the preferences. Instead of dialing-in on precise estimates in a highly uncertain environment, our focus in this work is to use three common approaches (conditional logit, mixed logit, and latent class analysis) and identify broad differences in MWTP estimates to better improve future DCE efforts for valuation of manageable soil quality.

Results for the mixed logit models using the sample restrictions above are shown in Table 6. Results are similar to the standard conditional logit specification, except for the additional standard deviation parameter. For water infiltration and high compaction, the standard deviation coefficient is significant, suggesting the presence of preference heterogeneity even within the restricted sample. There is also heterogeneity in preferences for organic matter, though not for the low rental rate group, the conventional till group, and the uncertain future plan groups. There is no evidence of preference heterogeneity for medium compaction across any of the models.

Results for the mixed logit models using the estimated latent classes are shown in Table 7. Results are again similar, with significant preference heterogeneity in water infiltration and high compaction across the four classes, and less heterogeneity in preferences for water infiltration for the soil-apathetic and soil-conscious classes. There is again no significant preference heterogeneity for medium compaction.

Table 6: Mixed Logit Estimation Results

		Rental Rate Groups			Tillage Groups		Future Plan Groups			Topography Groups	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Base	Low Rental Rate	Medium Rental Rate	High Rental Rate	Conventional	No-till/Strip-till	Self	Other	Uncertain	Level	Slope
Means											
Rental Rate	-0.368***	-0.465***	-0.477***	-0.292***	-0.436***	-0.281***	-0.398***	-0.41***	-0.411***	-0.259***	-0.412***
	(0.041)	(0.082)	(0.086)	(0.079)	(0.054)	(0.083)	(0.054)	(0.086)	(0.111)	(0.079)	(0.05)
Water Infiltration	9.686***	9.228***	10.144***	10.758***	9.847***	8.281***	9.806***	6.626***	12.839***	10.1***	9.631***
	(1.008)	(1.895)	(2.078)	(1.831)	(1.366)	(1.856)	(1.356)	(1.919)	(3.518)	(2.023)	(1.257)
Organic Matter	0.687***	0.714***	0.593***	0.614***	0.584***	0.933***	0.713***	0.564***	0.596***	0.79***	0.675***
	(0.068)	(0.128)	(0.135)	(0.142)	(0.08)	(0.161)	(0.092)	(0.142)	(0.179)	(0.144)	(0.084)
High Compaction	-2.853***	-3.025***	-2.603***	-2.601***	-2.749***	-3.183***	-2.632***	-2.962***	-3.706***	-2.563***	-3.037***
	(0.226)	(0.474)	(0.451)	(0.448)	(0.296)	(0.501)	(0.278)	(0.507)	(0.893)	(0.412)	(0.302)
Medium Compaction	-1.038***	-0.912***	-0.956***	-0.863***	-0.966***	-1.124***	-1.095***	-0.803***	-1.252***	-1.081***	-1.029***
	(0.111)	(0.21)	(0.224)	(0.214)	(0.139)	(0.239)	(0.146)	(0.222)	(0.314)	(0.228)	(0.135)
Field A Intercept	0.078	-0.145	0.729**	-0.424	0.393*	-0.814**	-0.13	0.829**	0.335	-0.59*	0.348*
	(0.158)	(0.323)	(0.33)	(0.301)	(0.202)	(0.338)	(0.208)	(0.354)	(0.404)	(0.304)	(0.196)
Field B Intercept	0.213	0.444*	0.635**	-0.391	0.381**	-0.243	0.081	0.904***	0.323	-0.509*	0.535***
	(0.138)	(0.266)	(0.292)	(0.27)	(0.177)	(0.288)	(0.184)	(0.301)	(0.352)	(0.278)	(0.17)
Standard Deviations											
Water Infiltration	8.693***	8.124***	7.79***	8.767***	9.697***	8.952***	9.61***	7.062***	10.698***	10.02***	8.692***
	(0.727)	(1.163)	(1.353)	(1.283)	(0.986)	(1.87)	(1.057)	(1.23)	(2.145)	(1.58)	(0.812)
Organic Matter	0.38***	0.283	0.35**	0.544***	0.185	0.504***	0.434***	0.364**	0.08	0.489***	0.384***
	(0.109)	(0.213)	(0.151)	(0.15)	(0.141)	(0.186)	(0.13)	(0.157)	(0.739)	(0.189)	(0.123)
High Compaction	1.789***	2.023***	1.495***	1.953***	1.785***	1.55***	1.71***	1.621***	1.849***	1.77***	1.867***
	(0.209)	(0.395)	(0.34)	(0.506)	(0.255)	(0.438)	(0.226)	(0.393)	(0.6)	(0.413)	(0.238)
Medium Compaction	0.117	0.145	0.233	0.041	0.009	0.309	0.069	0.069	0.514	0.46	0.104
	(0.137)	(0.191)	(0.304)	(0.298)	(0.186)	(0.336)	(0.168)	(0.251)	(0.406)	(0.346)	(0.141)
Observations	2072	530	466	580	1258	474	1181	428	354	577	1367
Log-Likelihood	-1603.690	-425.047	-354.779	-436.740	-966.634	-379.356	-934.794	-337.904	-242.133	-447.958	-1057.480
AIC	3229.379	872.095	731.557	895.479	1955.268	780.711	1891.588	697.807	506.266	917.916	2136.960

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Mixed Logit Estimation Results: Latent Class Analysis

	(1) Soil-Apathetic Class	(2) Soil-Conscious Class	(3) Moderate Class	(4) Uninformed Class
Means				
Rental Rate	-0.374***	-0.308***	-0.398***	-0.377***
	(0.101)	(0.093)	(0.065)	(0.086)
Water Infiltration	11.322***	11.665***	10.018***	6.360***
	(2.371)	(2.442)	(1.557)	(1.938)
Organic Matter	0.553***	0.848***	0.563***	0.745***
	(0.150)	(0.172)	(0.106)	(0.160)
High Compaction	-2.581***	-3.284***	-2.882***	-2.831***
	(0.488)	(0.526)	(0.366)	(0.496)
Medium Compaction	-1.166***	-1.383***	-0.894***	-0.900***
	(0.269)	(0.267)	(0.170)	(0.233)
Field A Intercept	-0.572	-0.048	0.278	0.263
	(0.376)	(0.355)	(0.251)	(0.340)
Field B Intercept	-0.339	0.018	0.313	0.512*
	(0.327)	(0.317)	(0.219)	(0.299)
Standard Deviations				
Water Infiltration	9.714***	9.242***	7.756***	9.110***
	(1.665)	(1.61)	(1.031)	(1.438)
Organic Matter	0.137	0.476*	0.468***	0.627***
	(0.162)	(0.247)	(0.145)	(0.178)
High Compaction	1.385***	1.727***	1.680***	1.774***
	(0.439)	(0.528)	(0.276)	(0.390)
Medium Compaction	0.090	0.049	0.047	0.044
	(0.261)	(0.271)	(0.206)	(0.304)
Observations	354	432	820	466
Log-Likelihood	-275.696	-303.367	-631.037	-374.968
AIC	573.393	628.734	1284.074	771.936

Note: *p<0.1; **p<0.05; ***p<0.01

5 Willingness-To-Pay Simulations

After estimating preference parameters for various subsamples and latent classes, we calculate marginal willingness to pay (MWTP) using a standard approach (Haab and McConnell, 2002):

$$WTP = -\frac{\beta}{\gamma} \cdot \Delta \cdot \rho, \tag{6}$$

where β is the coefficient on water infiltration, organic matter, or compaction (or a distribution defined by the mean and standard deviation coefficients on the same parameters), and γ is the coefficient on the rental rate. The ratio of these coefficients is the mean willingness-to-pay (MWTP) for a unit change in a specific attribute. For non-unit changes, we can multiply the ratio by any value of Δ, which is the magnitude of the change. The monetary vehicle in DCEs is typically continuous and thus varies by a natural unit: the dollar. In our case, rental rate varies by increments of \$10, and we must therefore multiply the ratio and Δ by $\rho = 10$ to translate MWTP to normal dollar terms.[12]

Setting $\Delta = 1$ in our context is not necessarily realistic nor helpful, since a full unit change might not be possible in the study area. Instead, we base our MWTP estimates on realistic soil quality changes attained in our study area. A team of soil scientists conducted a longitudinal study of soil quality measures in the watershed of the Brazos River in central Texas, taking repeated measurements of soil quality across farms under different management regimes (Bagnall and Morgan, 2021). See Table 8 for median soil quality measures under three different tillage regimes: conventional-till, no-till, and a perennial grass system. Hydraulic conductivity is equivalent to what we present as water infiltration in the DCE. Bulk density is equivalent to what we categorize as compaction.[13] While there is no real difference in bulk density across the regimes, there is a clear increase in water infiltration and organic matter moving from conventional-till to no-till in our study area. It is also important to note that despite the small difference in bulk density across the regimes, it is still possible to achieve significant improvements in compaction levels for farmers in our area.

Table 8: Median Soil Quality Indicators For Study Area

Management Regime	Hydraulic Conductivity (cm/hr)	Bulk Density (g/cm^3)	Organic Matter (% by mass)
Conventional	1.33	1.38	2.06
No-till	2.01	1.42	2.29
Perennial	3.04	1.40	4.40

Source: Bagnall and Morgan (2021)

Based on the in-field measurements, we calculate the willingness-to-pay for a Δ change in soil quality based on the adoption of no-till. That is, we estimate the MWTP for an average conventional-till farm to achieve the average soil quality improvements associated with a typical improvement for farms in the area. We set $\Delta = 0.27$inches/hour for water infiltration.[14] We set

[12] Specifically, $MWTP = -\frac{\beta}{\gamma}$, but since the rental rate changes in tens of dollars, the denominator must be divided by 10 to convert to single dollars. Thus, $MWTP = -\frac{\beta}{\frac{\gamma}{10}} = -\frac{\beta}{\gamma} \cdot 10$

[13] By "equivalent", we mean it measures the same soil quality attribute, even if the units or labels are different.

[14] We convert the raw difference of 0.68cm/hour to an inch/hour measure by multiplying the measure by 0.393701.

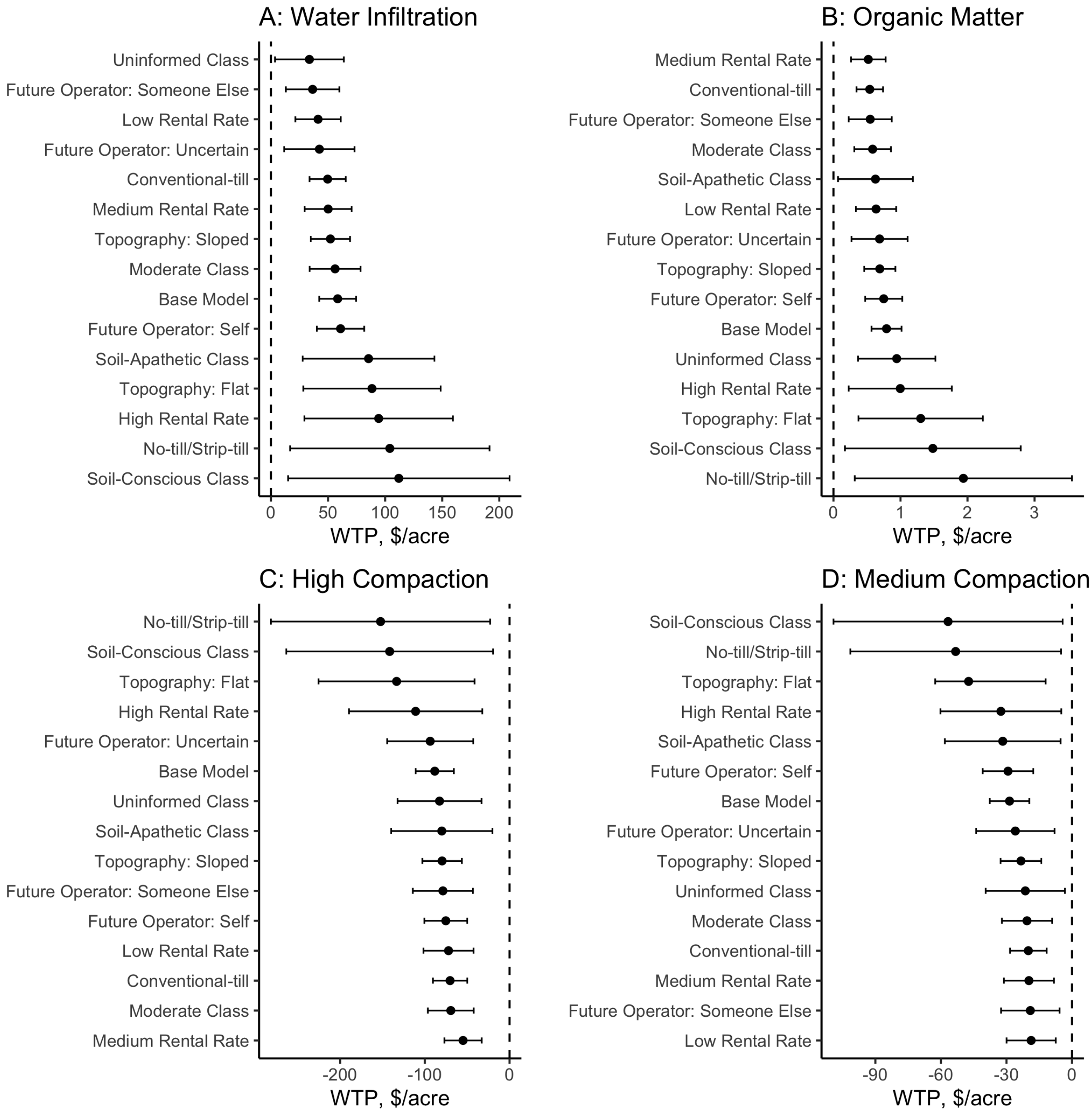
$\Delta = 0.04\%$ for organic matter. We leave the compaction indicators equal to one.

For both the conditional logit and mixed logit models, we calculate the 95% confidence intervals using the delta method. The delta method does not require any simulation for the conditional logit models, but because the mixed logit coefficients define a *distribution*, with the key distributional parameters also subject to sampling variance, the delta method requires both a closed form solution and simulation (Bliemer and Rose, 2013). Specifically, we take 1,000 random draws of the mean and standard error of the distribution of WTP over individuals, and use the average of the drawn means and standard errors of the distributions to define the asymptotic full distribution of WTP. As Bliemer and Rose (2013) note, the nature of variation over the WTP distribution *and* sampling variance of the key distributional parameters typically result in wide confidence intervals, which is what we find.

Results of the MWTP estimates for the conditional logit can be seen in Figure 4. Panel A shows MWTP for a realistic improvement in water infiltration by switching from conventional to no-till in our study area. Individuals in the soil-conscious latent class and the no-till/strip-till group are willing to pay the most, about \$100/acre. Respondents operating on flat topography are willing to pay more for water infiltration than respondents on sloped terrain, though the difference is not statistically significant. Indeed, no individual subsample or latent class has a significantly different MWTP than any other group. The same is true for the other soil quality characteristics (Panels B - D). In general, the conditional logit models suggest that farmers in the watershed of the Brazos River in Texas are willing to pay approximately \$50 - \$100/acre to improve water infiltration and approximately \$1 - \$2/acre to improve organic matter by adopting no-till. Farmers are willing-to-pay approximately \$100/acre to move from high to low compaction, and approximately \$40/acre to move from medium to low compaction.

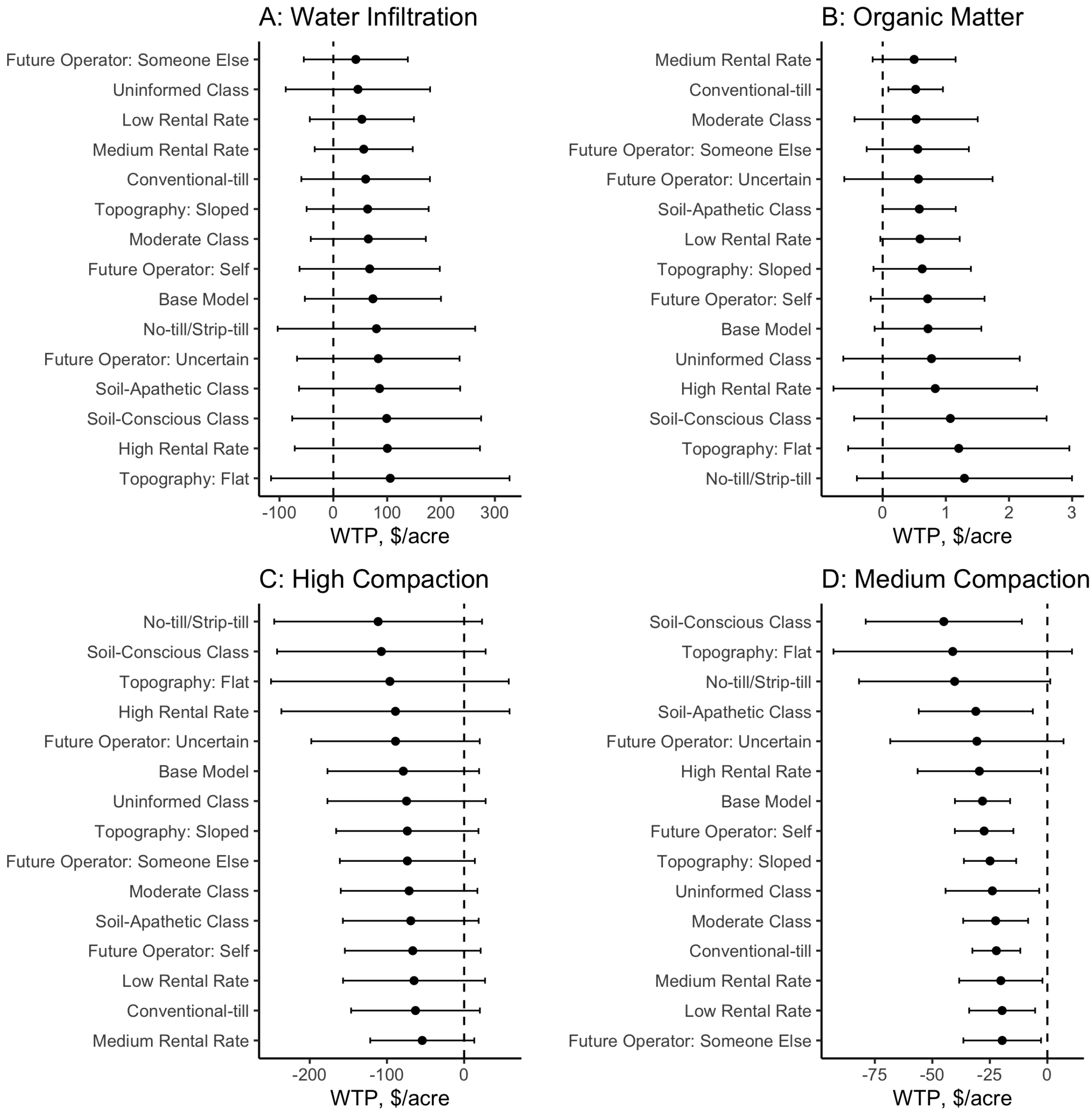
Results of the MWTP estimates for the mixed logit models can be seen in Figure 5. Perhaps unsurprisingly, the MWTP estimates are similar to the conditional logit estimates, but with much wider confidence intervals. While all MWTP estimates were significant at the 5% level, few of the MWTP estimates are significant at the same level for the mixed logit models, which is common for mixed logit models Bliemer and Rose (2013). The wide confidence intervals for the mixed logit models are a result of random preference parameters that vary over individuals and the key

Figure 4: Marginal Willingness-To-Pay By Model Specification: Conditional Logit



parameters that define that variation also exhibit natural sampling variance. In the context of the mixed logits, we find no strong evidence that farmers are willing to pay for improvements in soil quality associated with adopting no-till. The full numerical MWTP results for the conditional logit and mixed logit models is presented in Tables A1 and A2, respectively.

Figure 5: Marginal Willingness-To-Pay By Model Specification: Mixed Logit



6 Policy Implications

The on-farm value of manageable soil quality characteristics has long been estimated using changes in crop revenues or input costs. This study is the first to directly measure the value of changes in manageable soil quality characteristics independent of changes in agricultural production. Our willingness-to-pay estimates can therefore be considered the perceived benefits of soil quality improvements to farmers in our study area. Our results have important policy implications.

Our results can be compared to realized benefits to identify any significant difference between perceived and realized benefits of improved soil quality. For example, recent work from the Soil Health Institute has focused on partial budget analysis, which estimates the explicit costs and benefits of soil health management. An average soil health management system resulted in some reduced expenses and additional revenue for a total benefit of $93.66 per acre for a typical corn operation in Iowa (**?**). They also estimate a total change in cost of $29.81 per acre. A direct comparison to our WTP results is not appropriate because of significant differences in inherent soil and agricultural characteristics between Texas and Iowa. Nonetheless, estimates from partial budget analyses and studies like ours can help policy makers identify potential gaps between potential and realized benefits.

For example, suppose a farmer in the Texas Blackland MLRA is considering switching from a conventional to no-till regime. Suppose further that the farmer has a medium compacted soil, and he expects no-till to result in average improvements in water infiltration, organic matter, and a move from medium to low compaction. According to our work, that farmer (on average) is willing to pay approximately $87 ($58 + $1 + $28 from the conditional logit, full sample results) per acre to improve his manageable soil quality. Suppose partial budget analysis indicates that the benefits per acre of this change in soil health characteristics is $150 per acre per year. This would be nearly twice the the stated preference estimate of $86 and it is only for a single year – soil health benefits in our study should reflect the value of those characteristics for up to five years. In other words, this would suggest that the perceived benefits are much smaller than the best estimates of the true financial benefit. Understanding the difference between these two estimates can help policy makers understand the need for better communication on the benefits of conservation practices and how such practices are marketed, funded, and targeted.

Even without a comparison to partial budget analysis, our results are an estimate of the total value of improvements in soil quality and are therefore important on their own. Partial budget analysis misses non-use values that could be important to farmers and are captured in choice experiments like ours. With or without partial budget analysis, our results should be compared with estimated of the costs of implementing conservation practices to be fully relevant. If the costs of implementing no-till on Texas Blackland Prairie are $100 per acre, then we find that on average, the marginal benefits of improved soil quality characteristics may not exceed the marginal costs, on average (assuming the $87 per acre benefit from above). However, we also find that farmers operating on flat topography are willing to pay $136 ($88 + $1 + $47) per acre to improve water infiltration and organic matter by the average amount from switching to no-till and moving from medium to low compaction. *These* farmers would need less incentive to adopt no-till than other groups, which could lead to more efficient funding decisions from the United States NRCS or Farm Service Agency.

7 Discussion and Limitations

We follow a set of best-practices outlined in Johnston et al. (2017), including administering focus groups, performing pilot studies, and refining our experimental design before deploying a survey with a discrete choice experiment to farmers in central Texas. The final survey was administered through the USDA National Agricultural Statistics Service (NASS) to guarantee a representative and random sample in our study area.

We estimate several models to capture both the population-level preferences and the heterogeneous preferences that exist within sub-groups. We find that there are few differences in soil quality and rental rate preferences across groups based on their local rental rates, tillage practices, future plans, topography, or soil health attitudes.

When considering the average change in soil health characteristics that has been achieved by farmers in our study area moving from conventional tillage to no-till, we find that farmers in our study area are willing to pay approximately $58 per acre to improve water infiltration, $1 per acre to improve organic matter, $88 per acre to move from high to low compaction, and $29 per acre to move from medium to low compaction. The conditional logit results suggest statistically significant MWTP estimates, while the larger standard errors for the mixed logit models yield mostly insignificant estimates.

The significant difference in the estimated MWTP between organic matter and the other soil health characteristics deserves more attention. It may be the case that farmers truly value improvements in water infiltration 60 times more than a comparable improvement in organic matter.

If the majority of farmers are satisfied with the prevailing average organic matter levels in their area but are unsatisfied with some levels of water infiltration, this could be the case. Alternatively, farmers may be more comfortable with the way water infiltration was presented in the DCE (as inches absorbed per hour) than organic matter (as percent by soil mass). The way indicators of environmental quality are measured and presented is important (see Boyd et al. (2015) for evidence), and future work should experiment with alternative soil quality indicators to test how soil quality measurement affects valuation efforts.

For many respondents, the estimated WTP measures are larger than the prevailing rental rates across the study area. While this may raise concerns of a possible failure of the scope test, we speculate that it may be rational to expect WTP per acre measures that are larger than the rental rate per acre. The rental rate is an annual cost, while investments in soil health may be fixed, or at least variable for only a short time period. For example, to engage in strip-till, a farmer would need specialized tillage equipment which could be a substantial investment. It is not necessarily helpful to compare the WTP estimates directly to the prevailing rental rates. Rather, future work should be focused on comparing WTP estimates with the marginal costs of adopting soil-health practices that could achieve improvements in manageable soil health characteristics. A rational farmer should equate expected marginal costs with expected marginal benefits, and we only provide estimates of the marginal benefits in this work.

To our knowledge, we are the first study to estimate the willingness-to-pay for changes in soil quality characteristics using a discrete choice experiment. As such, we have learned important lessons that future researchers should keep in mind. First, we have concerns that our pivoted design on the rental rate would be better if we used an *online* survey. In an online format, each rental rate level could immediately pivot from a respondent's response, but in the paper format we were forced to use a generic $10 pivot and were not able to display an actual dollar amount.[15] This could bias the estimated coefficient(s) on rental rate towards zero, and thus bias the estimates of WTP upwards. Second, we encourage replication of our work in other regions. Our results are not likely to be externally valid for other areas with different inherent soil quality characteristics. The marginal benefits of improvement of manageable characteristics are likely dependent on the local

[15]On the other hand, we are cognizant that response rates may decline in online surveys, relative to paper surveys.

inherent conditions. For example, farmers in Iowa probably value changes in water infiltration quite differently than farmers in our study area.

Nonetheless, in this study we provide novel estimates of the marginal benefits of manageable soil quality improvement for farmers in central Texas. The estimated benefits are not directly tied to production output, as has been the dominant method of valuation for more than half a century (Ciriacy-Wantrup, 1947). We find evidence that farmers are willing to pay to improve manageable soil health, and while some groups are willing to pay more than others, we hope future valuation work continues to acknowledge that there is more to the value of soil than what it produces.

References

Aizaki, H. (2012). Basic functions for supporting an implementation of choice experiments in r. *Journal of statistical software*, 50:1–24.

Akaike, H. (1998). Information theory and an extension of the maximum likelihood principle. In *Selected papers of hirotugu akaike*, pages 199–213. Springer.

Bagnall, D. K., McIntosh, W. A., Morgan, C. L., Woodward, R. T., Cisneros, M., Black, M., Kiella, E. M., and Ale, S. (2020). Farmers' insights on soil health indicators and adoption. *Agrosystems, Geosciences & Environment*, 3(1):e20066.

Bagnall, D. K. and Morgan, C. L. (2021). Slakes and 3d scans characterize management effects on soil structure in farm fields. *Soil and Tillage Research*, 208:104893.

Bandeen-Roche, K., Miglioretti, D. L., Zeger, S. L., and Rathouz, P. J. (1997). Latent variable regression for multiple discrete outcomes. *Journal of the American Statistical Association*, 92(440):1375–1386.

Barbier, E. B. (1990). The farm-level economics of soil conservation: the uplands of java. *Land economics*, 66(2):199–211.

Barrett, S. (1991). Optimal soil conservation and the reform of agricultural pricing policies. *Journal of Development Economics*, 36(2):167–187.

Bazzani, C., Palma, M. A., and Nayga Jr, R. M. (2018). On the use of flexible mixing distributions in wtp space: an induced value choice experiment. *Australian Journal of Agricultural and Resource Economics*, 62(2):185–198.

Bliemer, M. C. and Rose, J. M. (2013). Confidence intervals of willingness-to-pay for random coefficient logit models. *Transportation Research Part B: Methodological*, 58:199–214.

Boyd, J., Ringold, P., Krupnick, A., Johnson, R., Weber, M., and Hall, K. M. (2015). Ecosystem services indicators: improving the linkage between biophysical and economic analyses. *Resources for the Future Discussion paper*, pages 15–40.

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., et al. (2018). Soil quality–a critical review. *Soil Biology and Biochemistry*, 120:105–125.

Burt, O. R. (1981). Farm level economics of soil conservation in the palouse area of the northwest. *American journal of agricultural economics*, 63(1):83–92.

Carson, R. T. and Louviere, J. J. (2011). A common nomenclature for stated preference elicitation approaches. *Environmental and Resource Economics*, 49(4):539–559.

Chinedu, O., Sanou, E., Tur-Cardona, J., Bartolini, F., Gheysen, G., and Speelman, S. (2018). Farmers' valuation of transgenic biofortified sorghum for nutritional improvement in burkina faso: A latent class approach. *Food Policy*, 79:132–140.

Ciriacy-Wantrup, S. V. (1947). Capital returns from soil-conservation practices. *Journal of farm economics*, 29(4):1181–1196.

Collins, L. M. and Lanza, S. T. (2009). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*, volume 718. John Wiley & Sons.

de Bekker-Grob, E. W., Donkers, B., Jonker, M. F., and Stolk, E. A. (2015). Sample size requirements for discrete-choice experiments in healthcare: a practical guide. *The Patient-Patient-Centered Outcomes Research*, 8(5):373–384.

Dominati, E., Mackay, A., Green, S., and Patterson, M. (2014). A soil change-based methodology for the quantification and valuation of ecosystem services from agro-ecosystems: a case study of pastoral agriculture in new zealand. *Ecological Economics*, 100:119–129.

Groothuis, P. A., Mohr, T. M., Whitehead, J. C., and Cockerill, K. (2017). Endogenous consequentiality in stated preference referendum data: The influence of the randomly assigned tax amount. *Land Economics*, 93(2):258–268.

Haab, T. C. and McConnell, K. E. (2002). *Valuing Environmental and Natural Resources : The Econometrics of Non-market Valuation*. New Horizons in Environmental Economics. Edward Elgar Publishing, Cheltenham, U.K.

Hanley, N., MacMillan, D., Wright, R. E., Bullock, C., Simpson, I., Parsisson, D., and Crabtree, B. (1998). Contingent valuation versus choice experiments: estimating the benefits of environmentally sensitive areas in scotland. *Journal of agricultural economics*, 49(1):1–15.

Hansen, L. and Hellerstein, D. (2007). The value of the reservoir services gained with soil conservation. *Land economics*, 83(3):285–301.

Hansen, L. and Ribaudo, M. (2008). Economic measures of soil conservation benefits: Regional values for policy assessment. *USDA Technical Bulletin*, (1922).

Hensher, D. A. and Rose, J. M. (2007). Development of commuter and non-commuter mode choice models for the assessment of new public transport infrastructure projects: a case study. *Transportation Research Part A: Policy and Practice*, 41(5):428–443.

Hess, S. and Rose, J. M. (2009). Should reference alternatives in pivot design sc surveys be treated differently? *Environmental and Resource Economics*, 42(3):297–317.

Hole, A. R. (2015). DCREATE: Stata module to create efficient designs for discrete choice experiments. Statistical Software Components, Boston College Department of Economics.

Holmes, T. P., Adamowicz, W. L., and Carlsson, F. (2017). Choice experiments. In Boyle, K. J., Brown, T. C., and Champ, P. A., editors, *A Primer on Nonmarket Valuation*, pages 133–186. Springer Netherlands.

Johnson, F. R., Kanninen, B., Bingham, M., and Özdemir, S. (2006). Experimental design for stated-choice studies. In *Valuing environmental amenities using stated choice studies*, pages 159–202. Springer.

Johnston, R. J., Boyle, K. J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T. A., Hanemann, W. M., Hanley, N., Ryan, M., Scarpa, R., et al. (2017). Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists*, 4(2):319–405.

Jonsson, J. O. G. and Daviosdottir, B. (2016). Classification and valuation of soil ecosystem services. *Agricultural Systems*, 145:24–38.

King, D. A. and Sinden, J. (1988). Influence of soil conservation on farm land values. *Land Economics*, 64(3):242–255.

Lal, R. (2014). Societal value of soil carbon. *Journal of Soil and Water Conservation*, 69(6):186A–192A.

Lee, L. K. (1980). The impact of landownership factors on soil conservation. *American journal of agricultural economics*, 62(5):1070–1076.

Linzer, D. A., Lewis, J. B., et al. (2011). polca: An r package for polytomous variable latent class analysis. *Journal of statistical software*, 42(10):1–29.

McConnell, K. E. (1983). An economic model of soil conservation. *American journal of agricultural economics*, 65(1):83–89.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, pages 105–142.

Murphy, J. J., Allen, P. G., Stevens, T. H., and Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics*, 30(3):313–325.

Plaas, E., Meyer-Wolfarth, F., Banse, M., Bengtsson, J., Bergmann, H., Faber, J., Potthoff, M., Runge, T., Schrader, S., and Taylor, A. (2019). Towards valuation of biodiversity in agricultural soils: A case for earthworms. *Ecological Economics*, 159:291–300.

Rose, J. M. and Bliemer, M. C. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, 29(5):587–617.

Scarpa, R., Campbell, D., and Hutchinson, W. G. (2007). Benefit estimates for landscape improvements: sequential bayesian design and respondents' rationality in a choice experiment. *Land Economics*, 83(4):617–634.

Schwarz, G. et al. (1978). Estimating the dimension of a model. *The annals of statistics*, 6(2):461–464.

Seitz, W. D. and Swanson, E. R. (1980). Economics of soil conservation from the farmer's perspective. *American Journal of Agricultural Economics*, 62(5):1084–1088.

Train, K. (2016). Mixed logit with a flexible mixing distribution. *Journal of choice modelling*, 19:40–53.

Train, K. and Wilson, W. W. (2008). Estimation on stated-preference experiments constructed from revealed-preference choices. *Transportation Research Part B: Methodological*, 42(3):191–203.

Unger, P. W. and Kaspar, T. C. (1994). Soil compaction and root growth: a review. *Agronomy Journal*, 86(5):759–766.

A Appendix

A.1 Survey Refinement

The initial survey instrument was developed in late 2018 and early 2019 using information from focus groups and cognitive interviews with local farmers and students. Pilot physical surveys were distributed on June 18^{th} and June 20^{th}, 2019, and the online survey was distributed via *Qualtrics*[16]

[16] https://www.qualtrics.com

Table A1: Willingness-to-pay by model/group: Conditional Logit

Model/Group	Water Infiltration	Organic Matter	High Compaction[a]	Medium Compaction[a]
Base Model	58.4	0.79	-88.26	-28.6
	(42.27, 74.53)	(0.57, 1.02)	(-110.78, -65.75)	(-37.66, -19.55)
Low Rental Rate	41.23	0.64	-72.02	-18.7
	(21.33, 61.12)	(0.34, 0.94)	(-101.54, -42.51)	(-29.95, -7.44)
Medium Rental Rate	50.06	0.52	-54.87	-19.72
	(29.49, 70.63)	(0.26, 0.78)	(-76.93, -32.81)	(-31.15, -8.28)
High Rental Rate	94.35	1	-110.87	-32.55
	(29.31, 159.38)	(0.23, 1.77)	(-189.58, -32.17)	(-60.2, -4.9)
Conventional-till	49.62	0.54	-70.2	-19.99
	(33.75, 65.49)	(0.34, 0.74)	(-90.47, -49.93)	(-28.38, -11.6)
No-till/Strip-till	104.09	1.94	-152.25	-53.26
	(16.72, 191.46)	(0.32, 3.56)	(-281.6, -22.89)	(-101.47, -5.04)
Future Operator: Self	60.95	0.75	-75.23	-29.3
	(40.21, 81.68)	(0.47, 1.03)	(-100.48, -49.98)	(-40.89, -17.72)
Future Operator: Someone Else	36.45	0.55	-78.65	-19.08
	(13.05, 59.85)	(0.23, 0.87)	(-114.18, -43.12)	(-32.49, -5.67)
Future Operator: Uncertain	42.39	0.69	-93.65	-25.94
	(11.58, 73.19)	(0.27, 1.11)	(-144.46, -42.85)	(-43.89, -7.98)
Topography: Flat	88.45	1.3	-133.33	-47.33
	(28.28, 148.62)	(0.37, 2.23)	(-225.42, -41.24)	(-62.61, -12.05)
Topography: Sloped	52.05	0.69	-79.63	-23.36
	(34.86, 69.24)	(0.46, 0.92)	(-102.96, -56.29)	(-32.69, -14.04)
Soil-Apathetic Class	85.47	0.63	-79.95	-31.7
	(27.76, 143.17)	(0.07, 1.18)	(-139.77, -20.14)	(-58.2, -5.21)
Soil-Conscious Class	111.97	1.48	-141.52	-56.74
	(14.98, 208.97)	(0.17, 2.79)	(-263.59, -19.45)	(-109.19, -4.28)
Moderate Class	56.13	0.58	-69.34	-20.61
	(33.85, 78.41)	(0.31, 0.86)	(-96.43, -42.25)	(-32.1, -9.12)
Uninformed Class	33.62	0.94	-82.64	-21.36
	(3.46, 63.79)	(0.37, 1.52)	(-132.25, -33.03)	(-39.52, -3.21)

Note: 95% confidence intervals in parentheses.
[a] *Willingness-to-pay to move to low compaction*

Table A2: Willingness-to-pay by model/group: Mixed Logit

Model/Group	Water Infiltration	Organic Matter	High Compaction[a]	Medium Compaction[a]
Base Model	73.49	0.72	-78.84	-28.19
	(-52.9, 199.89)	(-0.13, 1.56)	(-177.05, 19.38)	(-40.18, -16.19)
Low Rental Rate	52.94	0.59	-64.91	-19.65
	(-43.73, 149.61)	(-0.04, 1.22)	(-156.9, 27.08)	(-33.99, -5.31)
Medium Rental Rate	56.44	0.5	-54.3	-20.23
	(-34.61, 147.49)	(-0.16, 1.15)	(-121.7, 13.11)	(-38.34, -2.13)
High Rental Rate	100.3	0.83	-89	-29.56
	(-71.68, 272.29)	(-0.78, 2.44)	(-236.78, 58.79)	(-56.4, -2.71)
Conventional-till	59.96	0.52	-63.04	-22.18
	(-59.45, 179.36)	(0.09, 0.95)	(-146.47, 20.39)	(-32.6, -11.76)
No-till/Strip-till	80.02	1.29	-111.45	-40.31
	(-103.37, 263.41)	(-0.41, 3)	(-246.09, 23.19)	(-81.89, 1.26)
Future Operator: Self	67.44	0.71	-66.59	-27.5
	(-62.81, 197.7)	(-0.19, 1.61)	(-154.55, 21.37)	(-40.22, -14.77)
Future Operator: Someone Else	41.74	0.56	-73.56	-19.63
	(-54.86, 138.34)	(-0.25, 1.36)	(-161.04, 13.91)	(-36.51, -2.75)
Future Operator: Uncertain	83.47	0.57	-88.91	-30.64
	(-67.43, 234.36)	(-0.61, 1.74)	(-198.05, 20.23)	(-68.31, 7.03)
Topography: Flat	105.7	1.2	-96.2	-41.13
	(-115.76, 327.17)	(-0.55, 2.96)	(-250.21, 57.8)	(-92.98, 10.72)
Topography: Sloped	63.68	0.63	-73.63	-24.92
	(-49.68, 177.04)	(-0.15, 1.4)	(-165.84, 18.59)	(-36.29, -13.54)
Soil-Apathetic Class	85.86	0.58	-69.16	-31.1
	(-63.77, 235.49)	(0, 1.16)	(-157.11, 18.8)	(-55.91, -6.3)
Soil-Conscious Class	99	1.07	-107.25	-45.02
	(-76.43, 274.43)	(-0.45, 2.6)	(-242.34, 27.84)	(-78.97, -11.08)
Moderate Class	64.94	0.53	-71.33	-22.48
	(-41.9, 171.77)	(-0.45, 1.5)	(-159.84, 17.19)	(-36.6, -8.36)
Uninformed Class	45.63	0.77	-74.64	-23.9
	(-88.4, 179.66)	(-0.62, 2.17)	(-177.12, 27.84)	(-44.26, -3.54)

Note: 95% confidence intervals in parentheses.
[a] *Willingness-to-pay to move to low compaction*

beginning on August 9^{th}, 2019. Across both surveys, we received 42 usable responses (14 from the physical survey, 28 from the online survey). Select summary statistics are presented in Table A3. The average respondent farmer from the pilot sample is approximately 50 years old, and has approximately 25 years of experience in farming. Most farmers manage more rented acres than owned acres.

Table A3: Initial Survey Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Age	42	50.4	16.3	23	36	62.5	84
Years Farming	42	24.9	17.1	4	10	41.5	57
Acres Owned	39	957.1	1,826.0	0.0	130.0	670.0	7,995.0
Acres Rented	35	2,238.8	2,394.8	0.0	315.0	3,925.0	8,000.0

Farmers in the pilot sample engage in a variety of tillage practices. Most (approximately 43%) are engaged in neither strip- nor no-till practices. Approximately 23% of respondents were engaged in strip-till only, and the same proportion was engaged in no-till only. The remaining 11% have used both strip- and no-till on their operation. Using the pilot survey responses, we estimate a basic conditional logit model. Specifically, we assume the indirect utility V_{ijt} associated with respondent i choosing field j at time t is defined as:

$$V_{ijt} = \alpha_j + X'_{jt}\beta, \tag{7}$$

where α_j is a dummy variable equal to one if alternative j is Field A or Field B, and zero if alternative j is the opt-out option. The matrix X_{jt} contains information for the four chosen attributes of the choice experiment: water infiltration, organic matter, compaction, and rental rate. Compaction is the only categorical variable, with three levels: high, medium, and low. During the estimation process, the *low* compaction level is set as the base (omitted) category. Results of the pilot survey conditional logit are presented in Table A4. The sign of each estimated coefficient is as expected; as water infiltration and organic matter increase for a field, the probability of selecting that field increases, *ceteris paribus*. High and medium compacted fields are less likely to be chosen compared to to low compacted field, *ceteris paribus*. Finally, as the rental rate of a field increases, the probability of selected that field decreases.

Table A4: Pilot Survey Conditional Logit Estimation Results

	(1)
ASC	0.308
	(0.489)
Water Infiltration	8.304***
	(1.470)
Organic Matter	0.398***
	(0.098)
High Compaction[a]	−1.294***
	(0.239)
Medium Compaction[a]	−0.280*
	(0.165)
Price	−0.012***
	(0.005)
AIC	609.4
Observations	1,084
Log Likelihood	−298.688

Note: *p<0.1; **p<0.05; ***p<0.01

[a] *Omitted base category: low compaction*

After estimation of the conditional logit, take several steps to improve the final survey design, First, we suspected our pivot on the price variable was too small. In the new design, we increase the size of the pivot from \$5 to \$10. Second, we use the estimated coefficients in the pilot study as priors, and develop a D-optimal survey design. We use the *dcreate* package in Stata 14.1 (Hole, 2015) which maximizes the D-efficiency of the survey design. The D-efficiency of a survey design is:

$$D = \left[\left| \left[\sum_{n=1}^{N} \sum_{j=1}^{J} z'_{nj} P_{nj} z_{nj} \right]^{-1} \right|^{1/K} \right]^{-1}, \tag{8}$$

where n refers to a respondent, j refers to an alternative, K is the number of explanatory variables, and

$$P_{nj} = \frac{e^{x'_{nj}\beta}}{\sum_{j \in J} e^{x'_{nj}\beta}}, \tag{9}$$

which, from the conditional logit, is the probability that respondent n chooses alternative j, and

$$z_{nj} = x_{nj} - \sum_{j \in J} x_{nj} P_{nj}. \tag{10}$$

Calculating the D-efficiency of a survey design requires some prior knowledge of β, and is essentially how efficiently a survey design can identify the prior vector of coefficients. By substituting our pilot study $\hat{\beta}$ for β in equation 8, we find a matrix x_{nj} of size $(N \times J)$ by K of alternative levels combinations that maximizes the D-efficiency measure.

In maximizing the D-efficiency of the survey design, we also iterate over designs until we avoid conditions 1 and 2 from above. Further, we iterate until we find a design that has one dominated alternative to check for preference consistency, as described above. We thus create a D-efficient design that is not compromised by unrealistic alternative combinations and allows us to filter out respondents that are likely using some heuristic decision rule rather than making true utility-maximizing decisions.

Finally, we perform power calculations to determine our target sample size. Specifically, we find the minimum sample size N such that:

$$N > \left((z_{1-\beta} + z_{1-\alpha}) \sqrt{\sum_{\gamma k}} / \delta \right)^2 \tag{11}$$

where $\sum_{\gamma k}$ is the kth element of the diagonal of the variance-covariance matrix σ_γ of prior estimates δ. The statistical power can be set as $1 - \beta$, the significance level can be set at α, and then the $z-$score can be calculated from the normal distribution. This approach to finding the required sample size is specific to discrete choice experiments, and is outlined in de Bekker-Grob et al. (2015). This approach finds the minimum required sample size to identify each coefficient. Thus, for a range of β and α, we find the minimum sample size required for each coefficient. Results when $\alpha = 0.05$ and $1 - \beta = 0.8$ are shown in Table A5. The limiting variables that may hinder identification are the generic ASC and medium compaction. While the ASC may be useful, it is not integral to our research question. The primary coefficients of interest - water infiltration, organic matter, and rental rate - need at most 18 individuals for identification. Across all the subsamples in our analysis, we have more than 18 respondents and we are therefore confident of our estimated coefficients.

Table A5: Required Sample Sizes to Identify Effects

α	$1-\beta$	ASC	Water Infiltration	Organic Matter	Compaction: High	Compaction: Medium	Rental Rate
0.05	0.8	91.55	8.13	17.82	9.30	115.08	10.66

B Survey Instrument

Your Farm. Your Soil.

OMB No.0535-0264
Approval Expires: 4/30/2022
Project Code: 779
Survey ID: 1980
Version 48

United States Department of Agriculture

NATIONAL AGRICULTURAL STATISTICS SERVICE

TEXAS A&M UNIVERSITY

USDA/NASS - Texas
Southern Plains Region
PO Box 70
Austin, TX 78767-0070
Phone: 1-800-626-3142
Fax: 1-855-270-2725
Email: nassrfospr@usda.gov

Please make corrections to name, address, and ZIP Code, if necessary.

Why am I being asked to participate in this survey?

Soil health is critical to farm profitability and is a national concern. Yet, there is great uncertainty about farmers' perceptions regarding soil health. How do you assess the health of the soil on your farm? **How important is it to you?** What do you do to manage for soil health?

The purpose of this survey is to provide data for the first time about how farmers in your area think about soil health. The results of this survey will help researchers understand farmers' thoughts on soil health, which in turn will be used to provide guidance to policy makers on the best ways to achieve state and national soil-health goals. Your participation is important and greatly appreciated.

If you have specific questions regarding the content of this survey, please contact Richard Woodward, Professor, Dept. of Agricultural Economics, Texas A&M University, 979-845-5864, r-woodward@tamu.edu

Section 1: You and your operation		
Q1	How many years have you been farming?	101 ____________ years
Q2	How old are you?	102 ____________ years
Q3	Five years from now, which of the following do you think will be most likely?	103 1 ☐ I will still be operating the farm. 2 ☐ The farm will be operated by one or more relatives (children or other relatives). 3 ☐ The farm will be operated by a non-related farmer. 4 ☐ The farm will be converted into non-farm use. 5 ☐ Do not know.
Q4	When you eventually stop farming, which of the following do you think will be most likely?	104 1 ☐ The farm will be operated by one or more relatives (children or other relatives). 2 ☐ The farm will be operated by a non-related farmer. 3 ☐ The farm will be converted into non-farm use. 4 ☐ Do not know.
Q5	Did/do your parents farm? *(If No, skip to Q6)*	105 1 ☐ Yes 3 ☐ No
	a. Are they still farming?	106 1 ☐ Yes 3 ☐ No, stop farming 6 ☐ No, deceased
	b. Do you currently work with them?	107 1 ☐ Yes 3 ☐ No
	c. Have you ever worked with them?	108 1 ☐ Yes 3 ☐ No
Q6	Roughly, what share of your household income comes from farming?	109 1 ☐ 100% 2 ☐ 75% 3 ☐ 50% 4 ☐ 25% or less
Q7	Roughly, what percent of your working time is dedicated to farming?	110 1 ☐ 100% 2 ☐ 75% 3 ☐ 50% 4 ☐ 25% or less
Q8	Total acreage under management	111 ______ acres owned 112 ______ acres rented
Q9	Total acreage under management	113 _____ acres in row crops 114 ______ acres in pasture

Section 1: You and your operation (continued)

Q10 In 2019, how many acres did you plant in the following row crops?

a. Corn 115 __________ acres

b. Soybean 116 __________ acres

c. Wheat 117 __________ acres

d. Cotton 118 __________ acres

e. Grain Sorghum 119 __________ acres

f. Other 120 __________ acres

Q11 In 2019, did you use strip-till on any of the row crops that you manage?	121	1 ☐ Yes	3 ☐ No	
Q12 Do you intend to increase or decrease your use of strip-till in the future?	122	1 ☐ Increase	2 ☐ Decrease	3 ☐ No Change
Q13 In 2019, did you use no-till on any of the row crops that you manage?	123	1 ☐ Yes	3 ☐ No	
Q14 Do you intend to increase or decrease your use of no-till in the future?	124	1 ☐ Increase	2 ☐ Decrease	3 ☐ No Change
Q15 To what extent do you rely on a consultant, like an agronomist or entomologist, to help you make farm management decisions?	125	1 ☐ Extensively 3 ☐ Very Little	2 ☐ Somewhat 4 ☐ None; I do not use a consultant	

Section 2: Details on Base Field

We would like you to give details on 1 row-crop field that you manage. By "field," we mean an area that you manage as one piece in terms of tillage, planting, and harvesting. Please choose a field that you know well.

***If you do not use no-till or strip-till**, please choose a field with which you would be comfortable experimenting with alternative management practices.*

***If you do use no-till or strip-till**, please choose a field on which you might consider switching to conventional tillage.*

Give this field a name so it will be easy to remember (for example, "Johnson")

Q16 What county is this field located in?	201	_________________ county	
Q17 How many acres are in this field?	202	_________________ acres	
Q18 How many years have you been managing this field?	203	1 ☐ 0 – 5 years 3 ☐ 11 – 20 years	2 ☐ 6 – 10 years 4 ☐ 21 + years
Q19 Is this field owned or rented? *(If owned, skip to Q20)*	204	1 ☐ Rented	2 ☐ Owned
a. If rented, is the contract cash or shares?	205	1 ☐ Cash	2 ☐ Shares
b. If rented, how likely is it that you will be able to renew the lease for the next five years?	206	1 ☐ Very likely 3 ☐ Likely	2 ☐ Unlikely 4 ☐ Unknown
Q20 All crop(s) planted in 2019?	207	1 ☐ Corn 3 ☐ Wheat 5 ☐ Sorghum 7 ☐ Rice 9 ☐ Other (Specify: _____________________)	2 ☐ Soybeans 4 ☐ Cotton 6 ☐ Peanuts 8 ☐ Oats
Q21 Which tillage practice did you predominantly use on this field in 2019?	208	1 ☐ Conventional-till	2 ☐ No-till 3 ☐ Strip-till
Q22 Of the last 10 years, how many years have you used no-till or strip-till on this field?	209	_________years	

Section 2: Details on Base Field (continued)	
Q23 Did you use cover crops on this field in 2019?	210 1 ☐ Yes 3 ☐ No
Q24 Did you use manure on this field in 2019?	211 1 ☐ Yes 3 ☐ No
Q25 What type of irrigation was in the field in 2019?	212 1 ☐ None, Dryland 2 ☐ Center Pivot or Linear 3 ☐ Drip Tape 4 ☐ Furrow 5 ☐ Other (Specify: __________________)
Q26 Were there terraces on the field in 2019?	213 1 ☐ Yes 3 ☐ No
Q27 What is the general topography of the field?	214 1 ☐ Nearly level (Less than 1%) 2 ☐ Gently sloping (1-3%) 3 ☐ Moderately sloping (3-5%) 4 ☐ Strongly sloping (5-8%) 5 ☐ Steep (8-12%)
Q28 Which land type best describes this field?	215 1 ☐ Floodplain/bottomland 2 ☐ Hilly/upland 3 ☐ Neither
Q29 Approximately what percentage of this field is prone to flood for more than a day? (0% to 100%)	216 __________%
Q30 To what extent do you feel that suburban housing near the field affects the choices you make on that field?	217 1 ☐ No effect 2 ☐ A slight effect 3 ☐ A significant effect
Q31 To what extent do you feel that complaints from non-farming residents near the field affect the choices you make on that field?	218 1 ☐ No effect 2 ☐ A slight effect 3 ☐ A significant effect

Section 3: Soil health of your Base Field

Q32 *The table below lists seven changes in soil health characteristics that some farmers desire. For each of these, please check a box to indicate* ***how important*** *this change is to you for your* ***Base Field****.*

		Very Important	Fairly Important	Important	Slightly Important	Not Important at All	Don't Know
a. Increasing water infiltration	301	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
b. Increasing organic matter	302	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
c. Decreasing runoff	303	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
d. Decreasing erosion	304	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
e. Decreasing bulk density	305	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
f. Decreasing compaction	306	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
g. Increasing drainage	307	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐

Q33 *For each of the following indicators of soil health listed, please check a box to indicate you believe that* ***using no-till or strip-till on your Base Field*** *would increase or decrease the following soil characteristics?*

		Greatly Increase	Increase	Neither	Decrease	Greatly Decrease	Don't Know
a. Water infiltration	308	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
b. Organic matter	309	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
c. Runoff	310	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
d. Erosion	311	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
e. Bulk density	312	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
f. Compaction	313	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐
g. Drainage	314	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐

Section 4: Choices

In this section we ask 9 questions that are all quite similar. Together with responses from all the other respondents, your answers will help us understand how farmers feel about soil health, which will help policy makers develop appropriate policies.
Please answer all 9 questions by checking the box at the bottom of the column you choose.

*Suppose you are looking to expand your operation by renting an additional field of land. There are two fields on the market. Both fields are **identical to your base field** except for:*

- *Water infiltration*
- *Organic matter*
- *Compaction*
- *Rental rate*

*For both fields, the cash rental agreement would be **valid for at least 5 years**. In each of the 9 choice tables, identify the field you would choose to rent.*

Before beginning, **please indicate your estimate of the typical cash rental rate for a field *like your base field***:

400 ___________ ($/acre).

Refer to this as the "typical price"

Choice 1: Please identify the option you would choose.

	Field A	Field B	
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 3 hours	1 inch of standing water absorbs in 5 hours	Neither A nor B
Organic matter (%)	1%	2.5%	
Compaction	Restricts root growth partially	Restricts root growth substantially	
Cash rental rate ($/acre per year)	$10/acre more expensive than typical price	$10/acre less expensive than typical price	
I choose 401	1 ☐	2 ☐	3 ☐

Choice 2: Please identify the option you would choose.			
	Field A	Field B	Neither A nor B
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 3 hours	1 inch of standing water absorbs in 5 hours	
Organic matter (%)	2.5%	0.5%	
Compaction	Restricts root growth partially	Does not restrict root growth	
Cash rental rate ($/acre per year)	$10/acre more expensive than typical price	$10/acre less expensive than typical price	
I choose 402	1 ☐	2 ☐	3 ☐

Choice 3: Please identify the option you would choose.			
	Field A	Field B	Neither A nor B
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 3 hours	1 inch of standing water absorbs in 10 hours	
Organic matter (%)	0.5%	2.5%	
Compaction	Does not restrict root growth	Restricts root growth substantially	
Cash rental rate ($/acre per year)	$10/acre more expensive than typical price	$10/acre less expensive than typical price	
I choose 403	1 ☐	2 ☐	3 ☐

Choice 4: Please identify the option you would choose.			
	Field A	Field B	
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 10 hours	1 inch of standing water absorbs in 10 hours	Neither A nor B
Organic matter (%)	0.5%	0.5%	
Compaction	Does not restrict root growth	Restricts root growth partially	
Cash rental rate ($/acre per year)	$10/acre more expensive than typical price	$10/acre less expensive than typical price	
I choose 404	1 ☐	2 ☐	3 ☐

Choice 5: Please identify the option you would choose.			
	Field A	Field B	
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 3 hours	1 inch of standing water absorbs in 10 hours	Neither A nor B
Organic matter (%)	1%	2.5%	
Compaction	Restricts root growth partially	Restricts root growth substantially	
Cash rental rate ($/acre per year)	$10/acre less expensive than typical price	$10/acre more expensive than typical price	
I choose 405	1 ☐	2 ☐	3 ☐

Choice 6: Please identify the option you would choose.			
	Field A	Field B	
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 3 hours	1 inch of standing water absorbs in 5 hours	Neither A nor B
Organic matter (%)	2.5%	1%	
Compaction	Restricts root growth partially	Restricts root growth substantially	
Cash rental rate ($/acre per year)	$10/acre less expensive than typical price	$10/acre more expensive than typical price	
I choose 406	1 ☐	2 ☐	3 ☐

Choice 7: Please identify the option you would choose.			
	Field A	Field B	Neither A nor B
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 10 hours	1 inch of standing water absorbs in 10 hours	
Organic matter (%)	0.5%	1%	
Compaction	Restricts root growth substantially	Restricts root growth partially	
Cash rental rate ($/acre per year)	$10/acre less expensive than typical price	$10/acre more expensive than typical price	
I choose 407	1 ☐	2 ☐	3 ☐

Choice 8: Please identify the option you would choose.			
	Field A	Field B	Neither A nor B
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 3 hours	1 inch of standing water absorbs in 5 hours	
Organic matter (%)	2.5%	1%	
Compaction	Does not restrict root growth	Restricts root growth substantially	
Cash rental rate ($/acre per year)	$10/acre more expensive than typical price	$10/acre less expensive than typical price	
I choose 408	1 ☐	2 ☐	3 ☐

Choice 9: Please identify the option you would choose.			
	Field A	Field B	
Water infiltration (infiltration into deeply wetted soil)	1 inch of standing water absorbs in 10 hours	1 inch of standing water absorbs in 5 hours	Neither A nor B
Organic matter (%)	0.5%	1%	
Compaction	Does not restrict root growth	Restricts root growth substantially	
Cash rental rate ($/acre per year)	$10/acre less expensive than typical price	$10/acre more expensive than typical price	
I choose 409	1 ☐	2 ☐	3 ☐