Private Woodlands in Ohio: Understanding Landowners' Decision to Sell Woodlands and Participation in Forest Conservation Programs

Thesis

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By

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Abstract

The population of the Central Ohio region is increasing largely due to better economic prospects. The need for housing and related developments will likely go up as the population grows. Most of Ohio's forests are privately owned, and the anticipated developments could impact the current environment by altering the land use of privately owned woodlands. Landowner-level factors impacting changes in land cover and use are largely neglected while predicting these trends. In the first study, private woodland owners were surveyed in multiple counties in Central Ohio on their ownership characteristics, motivations for owning woodlands, demographic factors, and familiarity with ecosystem services account for those factors. The data was analyzed using a binary logistic regression model to identify key elements influencing woodland owners' willingness to sell their property at various price points. The study found that the choice to sell a property was significantly influenced by the landowners' age and residency on the property. Private woodland owners who owned their properties for hunting and amenity values were more likely to sell them. Additionally, landowners aware of the forest's capacity to clean the air expressed less interest in selling their property. On the other hand, landowners who used woodland for recreational activities were less likely to sell. The second study surveyed private woodland owners to determine their preferences for a hypothetical conservation program utilizing binary choice experiments and best-worst choice profiles. Woodland owners were asked to select the best and worst attributes of different programs and their willingness to enroll. Best-Worst scores, Conditional logistic, and Random Effects logistic regression were used to explain woodland owners' priorities. Best-Worst scores show that the highest revenue ($100 acre/year) was the most selected attribute in all choice profiles. A non-profit program structure and no withdrawal penalty are most desirable to woodland owners besides revenue at different amounts. Both regression models show that revenue is significant and positively associated with willingness to participate, and only a withdrawal penalty of $10/acre was not statistically significant. Private woodland owners are willing to sacrifice revenue for their preferred attributes in a program. For example, to go to a 30-year contract from a 60-year contract, woodland owners are willing to take $27.74 acre/year less in revenue. Landowners also chose different program attributes based on their groups. More educated landowners are significantly influenced by revenue, whereas landowners who own more land see management organization as a less critical attribute for enrollment decisions. Based on these findings of the first study, landowner groups who are more likely to sell their lands can be identified. The results of the second study can benefit policymakers in planning new conservation programs that ensure the supply of vital ecosystem services through private woodlands in Ohio.

Dedication

I dedicate this to my parents, who always believed in me and inspired me to embark on this journey.

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I want to thank my advisor Dr. Sayeed R. Mehmood, for giving me the opportunity to work with him. I am grateful for his immense support at every stage of my education at the Ohio State University. Especially during the difficult times of covid-19, he showed incredible patience and guided me towards successfully completing my work. I feel very fortunate that he allowed me to pursue an area of research I am passionate about.

I am also grateful to Dr. Roger A. Williams and Dr. G. Matthew Davies for agreeing to be a part of my advisory committee and supporting my work. I would also like to thank the School of Environment and Natural Resources for supporting my stay at the Ohio State University and providing a conducive environment for independent learning.

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Chapter 1. Introduction

Census data shows a trend of rapid population growth in the central Ohio region (U.S. Census Bureau, 2021). Consequently, the counties surrounding the Columbus metropolitan area face intense development pressure. Studies have previously shown that urbanization and urban population growth can lead to forest fragmentation and development in the fragmented lands (Mehmood & Zhang, 2001; Sampson & DeCoster, 2000). Rapid urbanization in Ohio can also lead to the conversion of private forests.

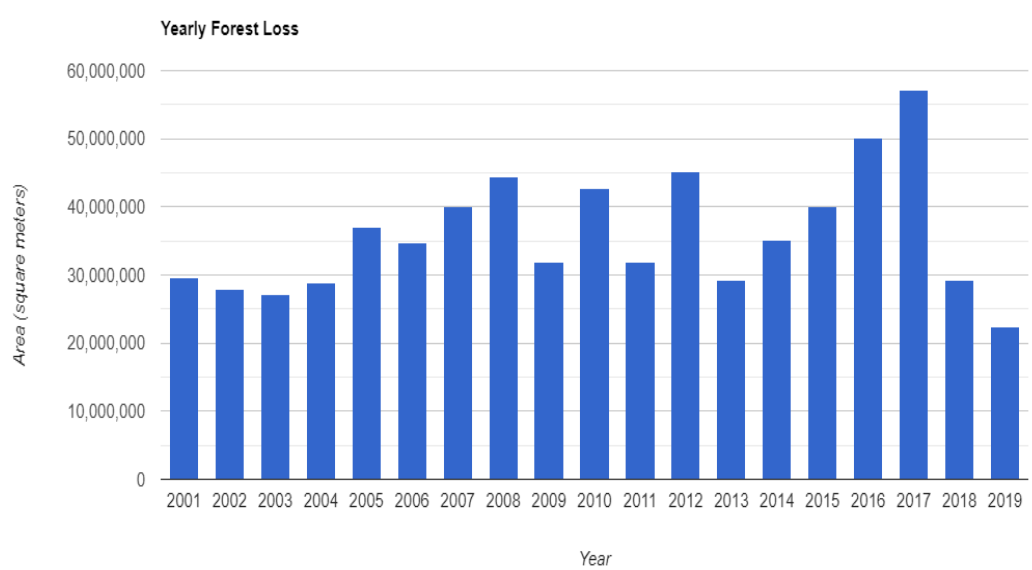

Figure 1.1 Forest loss in Central Ohio and surrounding counties from 2001-2019

Satellite images that cover large areas are commonly used to detect forest loss in the region of interest(Woodcock et al., 2020). Analysis of remotely sensed satellite images for Central Ohio and surrounding counties using the Google Earth Engine (G.E.E.) and Hansen dataset (Gorelick et al., 2017; Hansen et al., 2013) for global forest change shows that there has been a continuous forest loss in the area. Figure 1.1 shows the amount of forest land in square meters that was lost from 2001 to 2019.

Private woodland owners own most of the woodlands in Ohio (Albright et al., 2018). These forests supply essential products and ecosystem services. Some of these services include, but are not limited to, clean air, clean water, prevention of soil erosion, regulation of rainfall, and sequestration of atmospheric carbon (Aznar-Sánchez et al., 2018). Woodlands also improve biodiversity by providing habitat for many game and non-game wildlife species (Harder & Cameron, 2022; Mayer & Tikka, 2006; Mölder et al., 2021). If private woodland owners decide to sell their woodland because of the development pressure, the supply of these forest products and services would be affected.

This study focused on two main areas concerning the private woodlands in Central Ohio and its surrounding counties. Firstly, this study looked at private woodland owners' interest in selling their woodland, given that there are development pressures in Central Ohio. Woodland owners have different motivations and expectations from their lands (Bengston et al., 2011). So, when they are approached about selling their woodland, not every woodland owner will agree to sell their lands even though they are offered significantly higher prices for their land compared to the current market price. The decision to sell woodlands is similar to other private woodland management decisions, and multiple factors influence these decisions. Determining the factors that relate explicitly to Ohio's private woodland owners can help to classify lands that are in threat of being sold and converted.

Secondly, forest conservation programs can incentivize voluntary private woodland owners participation in conservation efforts (Langpap, 2004; SORICE et al., 2011). Different factors such as whether the landowners have a management plan for the woodland or if they harvest sawlogs can influence their decision to participate in conservation programs (Ma et al., 2012a). Therefore, the second area of this study was to identify forest conservation program attributes that influence landowner enrollment

1.2 Research Questions:

The objective of this study was to explore contributing factors of woodland owners' interest in selling their woodlands and their preferences for enrolling in forest conservation programs. The following research questions were considered in fulfilling the research objectives.

1. What factors influence private woodland owners' decision to sell forestlands in Ohio, U.S.A.?
2. Does potential revenue from hypothetical Forest Conservation Programs encourage private woodland owners to keep their woodlands?

1.3 Organization of the Thesis:

This thesis contains four chapters. The first chapter of the thesis gives a general introduction to the research area of private woodland and ecosystem services in the context of Central Ohio. The second chapter, titled "Woodlands In Ohio: Factors Of Private Woodland Owners' Decision To Sell Lands." discusses the contributing factors associated with the woodland owner's decision to sell woodlands at different price points. The third chapter, titled "Preferences And Willingness To Enroll In Woodland Conservation Program In Ohio, U.S.A." discusses landowner preferences in enrollment in forest conservation programs. The last chapter of the thesis discusses the overall conclusion and limitations of the study.

Chapter 2: Woodlands in Ohio: Factors of Private Woodland Owners' Decision to Sell Lands

Abstract:

Due to greater economic prospects, the population of the Central Ohio region is growing. As the population rises, the need for housing and related development will likely increase. Private woodland owners own most of Ohio's woodlands, and the projected developments can change the current landscape by converting private woodlands into a different land-use. Models that predict land-cover and land-use change often fail to account for landowner-level factors that influence this change. In this study, private woodland owners were surveyed in multiple counties in Central Ohio on their ownership characteristics, motivations for owning woodlands, demographic factors, and familiarity with ecosystem services. Binary logistic regression was performed on the survey data to find important factors contributing to woodland owners' decision to sell their land at different hypothetical price points. The results suggest that the Age of the landowners and ownership length significantly influenced landowners' decision to sell. Woodland owners who owned lands for their amenity values, hunting, and doing other recreational activities on the land were less likely to sell their lands. Also, landowners familiar with the forest's air purification services showed less interest in selling their land. Conversion of

woodlands can result in the loss of critical ecosystem services, and these factors should be incorporated into statewide conservation planning.

2.1 Background and Literature Review:

The Central Ohio region has seen a population boom from 1960 to 2017 (Millsap, 2022). While similar areas in the mid-west have seen economic downturns (Cocks & Johnson, 2021), the Central Ohio region has maintained economic growth (Millsap, 2022). It is projected that by 2050 the population in this region will reach 3 million from 2.2 million in the 2010s (Ozbilen et al., 2021). The Mid-Ohio Regional Planning Commission (MORPC) reports that this population growth is accompanied by increased jobs and demands for housing units (MORPC, 2018). This projected growth will impact the private woodlands in Ohio as it was seen that development pressure impacts private woodlands in the Eastern United States (Sampson & DeCoster, 2000). This development process can cause forest fragmentation, resulting in habitat loss and habitat degradation for several wildlife species.

Since most of the forested lands in the state of Ohio are privately owned, there is an increased probability that these lands could be developed to maximize economic return. It is crucial to discover how they are converted from one land use to another and what factors influence these changes. As private woodland owners are utility maximizers, they would choose any management decision, including the sale of their woodland, if it maximized their utility from the woodland (Shivan & Mehmood, 2012). Their decision would be influenced by multiple factors related to socio-economic characteristics, land characteristics, ownership motivations, and objectives (Joshi & Mehmood, 2011b; Ma et al., 2012a; G.C & Mehmood, 2010; Silver et al., 2015). This study focuses on the factors associated with private woodland owners deciding to sell their woodlands. According to the Food and Agriculture Organization of the United Nations (FAO), forest land is considered one acre or more that has at least 10% tree cover. Woodlands contain shrubs along with trees, effectively creating more than 10% tree cover (Oswalt et al., 2019). Private forests or woodlands are defined as forests that are owned by individuals, families, co-operatives, conservation organizations, or NGOs (Smith et al., 2018).

Around 9.6 million family forest owners own 272 million acres of forested area in the United States (Butler et al., 2016). About 95% of private forests are owned by individuals or families (Butler et al., 2016). So, these privately owned family forests are crucial for managing forestlands sustainably. Privately owned forests can be both industrial and nonindustrial. Industrial forests have different management goals and are inclined more toward timber production. The characteristics of family forests differ from other privately owned industrial forests or public forests. Management goals for family forests are usually for their amenity values, such as their beauty and role as a wild habitat, compared to their value in timber production (Butler & Leatherberry, 2004; Rittel & Webber, 1973). These diverse groups of forest owners are continuously increasing in numbers, and they control much of the future of the country's forests (Bengston et al., 2011).

Land use activities that either convert existing natural lands for human use or change the current use of an already disturbed land to a new user type have affected a large portion of the global lands (Foley et al., 2005). The urban land area has increased by a factor of 4.7 from 1945 to 2012 in the United States (Bigelow & Borchers, 2017). When demand for housing or commercial/industrial land increases, it can lead to the conversion of forest and agricultural lands to these new uses since financial returns from crops or timber production are no longer viable alternatives to new land uses to retain these lands. Furthermore, once this land conversion occurs, it rarely reverts to its original use as forest or agricultural land (Bigelow & Borchers, 2017). Polyakov & Zhang, (2008), also explain this through the traditional land use Ricardian rent theory, where lands are allocated to different uses based on expected return.

The Central Ohio region is one of the fastest-growing areas in the Midwest, and it is seeing continuous population growth (Gallemore et al., 2018; Munroe, 2010). With this development and population growth in the counties of central Ohio, there is a strong possibility that family-owned forested lands might also be developed and turned into either housing or agricultural lands (Koch et al., 2019). Ohio has a forest cover of about 8.5 million acres, and private forest landowners own 80% (6.78 million acres) of these forested lands(Albright et al., 2018; U.S. Forest Service, 2022). Of the 336,000 private forest landowners, 93% own less than 50 acres of land (Widmann et al., 2009). Because the private forest owners are the majority who decide the fate of forest cover in Ohio, how they would manage their forestland is important for the supply of timber and non-timber forest products and services. Developing forestland into other land-use types is essentially a land-use change. The drivers of land-use change can either be socio-ecological or socio-economic. Socio-ecological drivers come into play when vital ecosystem services and products are severely degraded from their previous form and the current land use is no longer viable (Lambin & Meyfroidt, 2010). Socio-economic drivers can be independent of ecological conditions. Exogenous changes in economic development, urbanization, or even globalization can have an impact on land management and can cause the development of land from one use to another (Lambin & Meyfroidt, 2010).

Geist & Lambin, (2002), also used the idea of proximate, underlying, and other causes that drive tropical deforestation, and in theory, they apply to any forest cover loss. Proximate causes are directly human linked, which impacts forest cover through the change in land use. Usually, they are local; for example, agricultural or infrastructure extension at a local level can cause forest land use to change and cause forest fragmentation. Underlying causes are systemic socio-economic causes, including economic, technological, cultural, demographic, and policy or institutional factors. Population growth as a demographic factor, environmental value changes as a cultural factor, urbanization, and industrialization as an economic factor can play the underlying causes of land-use change. There are other variables, including land characteristics (soil quality, location next to water resources), biophysical factors (soil fertility decline, forest fire), and social trigger events (war, epidemics/pandemics, abrupt shift in policy), that also cause a land-use to change in forested areas. As seen in most cases, instead of one specific factor, multiple factors play an essential role in changes in forestlands (Geist & Lambin, 2001).

Most land use change studies that project future land use utilizes past land use data for prediction. For predicting land-cover change in the southeastern United States, models use various explanatory factors, including population density, elevation and slope of the land parcel, distances from the road, and distance from the historical coal mining sites (Sohl & Sayler, 2008). Another study in western Washington used population density change and satellite images of past land use to predict the development on private forests (Kline et al., 2009). However, factors associated with private woodland owners themselves, who greatly influence where development might occur, were not considered.

Other studies have looked at landowner-level factors for the decision to convert woodlands. Poudyal et al., (2014), studied Tennessee landowners who converted their lands previously and found that age, gender, land tenure, and ownership size were important factors in their decision. Another study on Washington State's small forest landowners' intentions to develop forestland revealed that gender, education, having a forest plan, and proximity to development were guiding their decisions (Rozance & Rabotyagov, 2014). A similar study to find out factors of forest land sale in the Catskill watershed of New York found that landowners divided their land into multiple smaller parcels because of higher property taxes and sold parcels because they received a lucrative price offer for their land (Stone & Tyrrell, 2012). Another study on Massachusetts private woodland owners' land sale decisions found that younger (30-50 years old) landowners who saw forestlands as investments were more likely to sell their lands (Ma & Kittredge, 2011). On the other hand, those who used their forest for its amenity values were less likely to sell their lands.

The above studies show that woodland owner characteristics, land characteristics, and motivations behind owning woodland can influence the decision to sell or develop woodlands. However, there is a lack of studies that explicitly explores the intentions of selling private woodland in central Ohio. This current study was designed to identify the influencing factors of selling private woodlands in this region.

2.2 Materials and Methods:

2.2.1 Study Area:

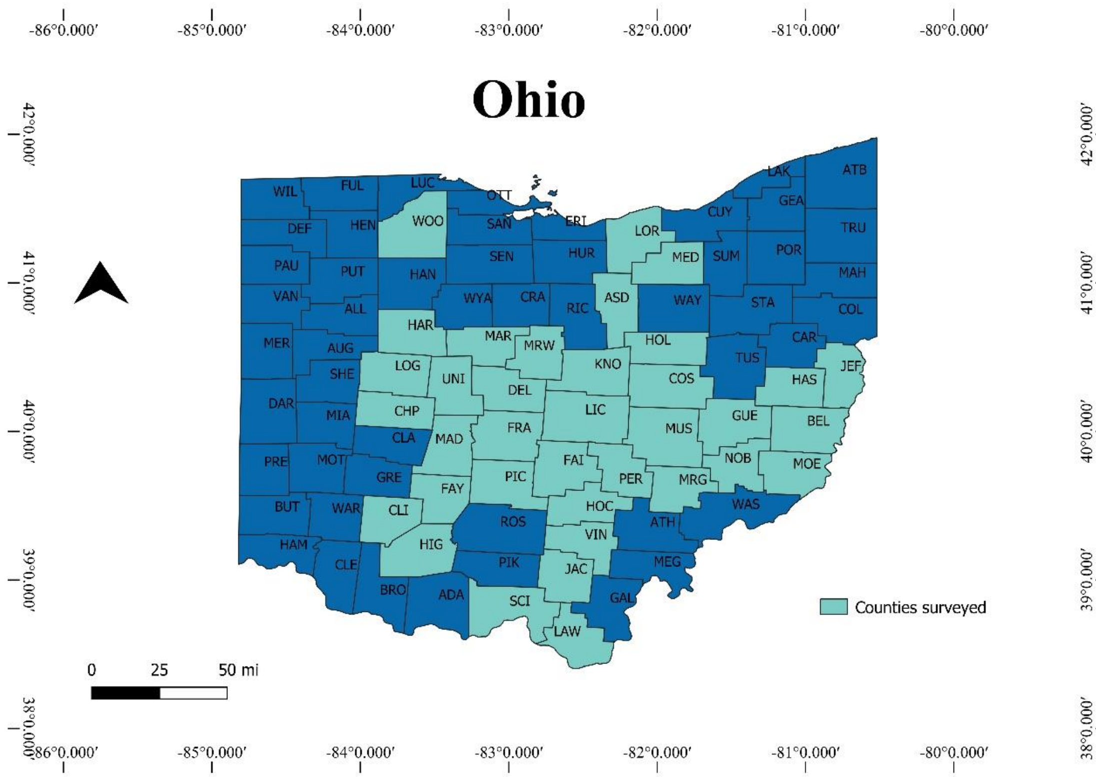

Figure 2.2 Counties in Ohio surveyed for the study

The focus of the study was to survey woodland owners who own woodlands in Central Ohio and its surrounding counties because most of the projected population growth and new developments will likely occur in this region (MORPC, 2018). Along with the central Ohio counties, Medina, and Lorain counties were include as part of the study since they are near Cleveland Metropolitan Area.

2.2.2 Econometric Model:

2.2.2.1 Random Utility Framework:

Random utility theory explains how woodland owners decide about their use and management of woodlands. Since 1980 there has been a shift towards modeling nonindustrial private woodland owners as utility maximizers rather than profit maximizers (Gregory et al., 2003). The utility is a fundamental concept in standard microeconomic theory where consumers choose from different bundles of goods and services. The exact process a decisionmaker (nonindustrial private forest owner) uses while choosing from a set of alternatives is unknown to the observer (Hess et al., 2018). A decisionmaker's choice can vary systematically or be unique to a decision maker. Because of that, a random element is introduced in the utility model, which expresses choices as probabilistic events. This combination of a random element with utility maximization is called a random utility model (RUM) (Hess et al., 2018). In a RUM, a decisionmaker expressed as n faces j alternatives where $j = 1,2, \ldots, j$. The utility of choosing j (U_{nj}) is only known to the decision maker but not to the observer. An alternative i will be chosen if and only if, $U_{ni} > U_{nj}\ \forall\ i \neq j$. Although, this utility cannot be observed directly, some attributes of the alternatives ($A\_nj \quad \forall\ j$) and some attributes of the decision maker (P_n) is observable. A representative utility function $V_{nj} = \mathrm{f}\left(A_{nj}, P_n\right)\ \forall\ j$ can be developed from these two types of attributes. The random utility U_{nj} can be decomposed as $U_{nj} = V_{nj} + \varepsilon_{nj}$ where ε_{nj} is a random error term (Train, 2009). The representative utility is a deterministic component (Bashir et al., 2020). This deterministic component of private forest owners' decisions that maximizes their utility can be explained by a set of observable owner-specific factors. So, nonindustrial private forest owner utility can be modeled as follows:

$$U_{nj} = f(S, LC, O, OP, E) + \varepsilon_{nj} \forall j$$

Here, S is sociodemographic variables, LC is land characteristic variables, O is ownership objectives, OP is 0wnership plan, and E is familiarity with the ecosystem services.

2.2.3 Variable Selection:

Multiple variables are of interest in modeling private woodland owner decisions. We can group these variables into multiple categories using relevant literature.

Sociodemographic: This group of variables (age, gender, education, income) contains important characteristics of nonindustrial private forest owners that are important predictors of forest owner behavior (Ruseva et al., 2014). For example, landowners with higher income and education are more likely to participate in silviculture activities (S. Joshi & Arano, 2009). Another study found that female forest owners show more risk-seeking behavior in harvesting decisions (Andersson, 2012).

Land Characteristics: Nonindustrial private forest owners' decisions also depend on the characteristics of the forestland they own (Tenure, Acquisition, Ownership size). A study that investigates private forest landowners' decision to supply woody biomass found that with an increase in ownership size, forest owners are more likely to supply bioenergy in the form of woody biomass (Joshi & Mehmood, 2011a).

Ownership objectives:

Ownership objectives are linked to timber harvest and silviculture activities (Karppinen, 1998). Multi-objective (financial, hunting/fishing, home.) owners have more than only financial incentives to manage forestlands; they use their forestland for other amenity values of a forest that are not monetary (Favada et al., 2009). Another study also supports the idea that urbanized forest owners use the property to enjoy peace and tranquility. So, they are less likely to use their forestland for income generation (Côté et al., 2017), meaning they would not consider converting their land for only monetary reasons.

Ownership Plan:

Although ownership plan/goal (e.g., To develop or not develop the forestland) can be shaped by the land characteristic of the forest itself (Stanislovaitis et al., 2015) but for this study, it is essential to know about the plan with the forestland since this would be the dependent variable for the regression analysis of this study. In the table below, the selected variables for this study are listed.

Table 2.1. Used variables in the study, modified from (Floress et al., 2019)

Variable	**Description**
Sociodemographic	
Age	Age of the woodland owner in years
Gender	Gender of the landowner
Education	Level of Education completed
Income	Household income in USD
Land Characteristic	
Residence	Whether the owner reside on property
Lot size	Amount of woodland owned
Number of parcels	How many disconnected parcels are owned
Land Acquisition	How the land was acquired
Ownership length	How long the land has been in the current ownership
Ownership structure	Whether land is owned by an individual, a family or multiple ownership
Public land	Whether the property is adjacent to public land
Ownership Objectives	
Amenity	Includes beauty, scenery, privacy, raise family, non-timber forest products
Conservation	Includes protecting nature, diversity, water, wildlife
Financial	Includes owning land for investment
Hunting	Includes owning land for hunting
Personal use of wood	Includes using wood from land
Recreation other than hunting	Includes using land for recreational activities other than hunting

continued

Table 2.1 continued

Timber	Includes owning land to manage for timber
Bequest	Conserve for future generation
Ownership plan	
Sell	if the landowner plans to sell the land at different price points
Selected Ecosystem services	Aesthetics, Biodiversity (Increase richness of plant and animal species), Carbon sequestration, Clean Water, Clean air Personal recreation (e.g., hunting, fishing, camping, wildlife watching), Providing fee-based recreation (e.g., hunting leases, ecotourism), Production of non-timber forest products (e.g., maple syrup), Soil erosion control, and Watershed management

In appendix A, the complete survey instrument is included.

2.2.4 Data Collection:

This study used the traditional mail survey for data collection since many of the older woodland owners would be unreachable in an electronic survey. The Ohio State University's Institutional Review Board (IRB) approved the survey instrument (appendix A), and the survey was sent to the woodland owners via mailings. For the survey deployment, a modified version of the widely used Dillman survey method was adopted (Dillman et al., 2014). This method uses multiple steps for collecting data in a mail survey. Before the survey instrument was sent to the landowners, a notification postcard indicated that they would receive a survey from the Ohio State University. The postcard outlined the nature of the research and why it was essential. Then the survey was sent out to the landowners a week after the notification via the postcard. The first page of the survey contained the cover letter for the survey. This letter clarified the survey questions and critical terms for better comprehension of the woodland owners. Respondents who returned the completed survey were taken out of the original landowner list, and non-respondents were sent the survey again.

This survey used random sampling of the landowners in Central Ohio. The list of landowners was selected from property tax rolls. The list contained both landowners who owned woodlands and did not own any woodlands but owned other types of lands. The participant selection criteria for this study were to own at least 4 acres of woodlands in Ohio. No written consent was obtained before the woodland owners received the survey. However, landowners voluntarily participated and returned the completed survey in business reply envelopes. Landowners were assured in the survey instrument that the data they entered into the survey would be kept anonymous. In addition, landowners were also asked to provide their email addresses if they wanted to be contacted for further communications or wanted a summary of the research outcomes using the survey data.

2.2.5 Statistical Analysis:

This study aimed to classify landowners based on their willingness to sell woodlands under different price scenarios. Accordingly, logistic regression analysis was used with the dependent variable of this study being the willingness to sell. Since this was a binary choice question, the dependent variable followed the logistic distribution. The choices are rooted in the random utility model (Greene, 2003). For forest landowner i with j choices, the random utility model is $U_{ij} = \boldsymbol{z}'_{ij}\beta + \varepsilon_{ij}$ where U_{ij} is the maximum utility given among all choices. So, the statistical model for choosing j is $\mathrm{Prob}\left(U_{ij} > U_{ik}\right)$ where $i \neq k$. Here, utility depends on components specific to the individual and the choices. Modifying from Joshi & Mehmood, (2011a) and Jr et al., (2013), if Y is the dependent variable which is explained by x independent variable, then the relationship between Y and x is given by $Y = \beta_0 + \beta_1 x$. The expected value of Y is given by $E(Y|x) = \beta_0 + \beta_1 x$. Since Y is dichotomous and follows a logistic distribution, the value of $E(Y|x)$ ranges from 0 to 1. So, the logistic regression model is

$$\pi(x) = E(Y|x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \qquad \text{(Eq. 2-1)}$$

For estimation, we need the likelihood function, which is given by the product of $\pi(x_i)$ (when $Y_i = 1$) and $1 - \pi(x_i)$ (when $Y_i = 0$). So, the likelihood function is

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i} \left[1 - \pi(x_i)\right]^{1-y_i} \qquad \text{(Eq. 2-2)}$$

The estimate of β is the value of β that maximizes equation 2-2. For that, the likelihood equations are used. These equations are

$$\sum [y_i - \pi(x_i)] = 0 \text{ for } \beta_0 \qquad \text{(Eq. 2-3)}$$

$$\sum x_{i[y_i - \pi(x_i)]} = 0 \text{ for } \beta_1 \qquad \text{(Eq. 2-4)}$$

There will be a likelihood equation for obtaining maximum likelihood estimation for each independent variable. Using the β values, we get the following logit equation

$$\hat{g}(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_j \qquad \text{(Eq. 2-5)}$$

Then using the maximum likelihood estimates of β values and x values, we get the probability of an event from the following equation

$$\hat{\pi}(x) = \frac{e^{\hat{g}(x)}}{1+e^{\hat{g}(x)}} \qquad \text{(Eq. 2-6)}$$

The coefficients of the logistic regression model cannot be directly interpreted similarly to a linear regression model (Scott et al., 1991). Since the study's goal was to classify landowners based on their interest in selling woodland, the marginal effects of each independent variable on the probability of class assignment were estimated (Joshi & Mehmood, 2011a).

Out of 2500 surveys that were sent, 663 people responded which results in a 26.5% response rate. Among the returned surveys, landowners who did not own any woodlands or owned less than 4 acres of woodland were removed from the analysis. Also, incomplete surveys with multiple blank answers were removed. However, surveys with missing values for the Age and Lot size variable were considered. Those missing values were imputed using the multivariate imputation by chained equations (mice) technique described in (Butler et al., 2016). For the imputation of the missing values, a package called mice in the R statistical environment was used (Van Buuren & Groothuis-

Oudshoorn, 2011). Finally, 380 surveys were used for the data analysis with an effective response rate of 15.2%.

Ownership motivation variables had 5 levels in the survey. Landowners indicated their motivation for owning using Strongly Agree, Agree, Neutral, Disagree, or Strongly Disagree. To convert them to binary variables, first, these levels were coded as Strongly Agree = 5, Agree = 4, Neutral = 3, Disagree = 2, and Strongly Disagree = 1. Then the average value of each of the ownership motivations was calculated. If a landowner's indicated level was higher than the average, then 1 (= Yes) was assigned for that ownership motivation. Otherwise, 0 (= No) was assigned. The same procedure was followed to convert the familiarity with ecosystem services variables to binary response. The coding for variable used in binary logistic regression model is given in Table 2.2.

Table 2.2 Coding of the variables used in logistic regression model

Variables	**Coding**
Dependent variable	
Sell at 30% higher than market price	Dummy variable: Yes = 1, No = 0
Independent variables	
Lot size	Continuous variable
Parcel	Categorical variable: 1 parcel= 1, 2 parcels=2, 3-5 parcels=3, 6-10 parcels= 4, more than 10 parcels= 5

continued

Table 2.2 continued

Ownership	Categorical variable: Individual= 1, Family= 2, Multiple ownership = 3
Acquisition	Categorical variable: Purchased = 1, Inherited = 2, Received as a gift = 3
Ownership Length	Continuous variable
Resident	Dummy variable: Resident on property = 1, Not Resident = 0
Land Sold	Dummy variable: Yes = 1, No = 0
Age	Continuous variable
Gender	Dummy variable: Male=1, Female= 0
Education	Dummy variable: College or more= 1, Otherwise= 0
Income	Dummy variable: More than $100,000= 1, Otherwise= 0
Amenity, Conservation, Financial Hunting, Personal Use, Recreation, Protect Environment, Timber, Bequest	Dummy variables: Landowner's indicated level higher than the average =1, Landowner's indicated level lower than the average = 0
Aesthetics, Biodiversity, Carbon Sequestration, Clean Water, Clean Air, Personal Recreation, Fee-based ecosystem service, Production of NTFP, Soil Erosion Control, Watershed Management	Dummy variables: : Landowner's indicated level higher than the average =1, Landowner's indicated level lower than the average = 0

2.3 Results:

2.3.1 Descriptive Statistics:

The summary statistic of the land characteristic variable is presented in Table 2.2. The mean area of woodlands ownership was 62.10 acres, with 4 acres being the smallest woodland and 1050 acres being the largest. Most owners owned one parcel of woodland (47.90%). The percentage of woodland owners that owned 2 parcels and 3-5 parcels were 27.60% and 23.20%, respectively. Very few woodland owners had more than 10 parcels. Furthermore, family (41.30%) and individual (55.50%) woodland owners comprised most of the woodland. Ownerships that comprised of multiple owners made up only 3.20% of the woodlands. Most of the woodlands were acquired through purchasing (76.10%), while 22.90% of woodlands were inherited. Among the surveyed woodland owners, 67.10% were residing on the property, and the remainder were absentee landowners. Only 18.40% of landowners had any forest management plans, and 6.80% of woodlands were near public lands. Table 2.3 summarizes the ownership plan of the woodland owners. Although only about half of the woodland owners (48.20%) received offers to sell their land in the last 5 years, most of them said that they would sell their woodlands if offered the current market price or even 10-20% higher than the market price. About 19% of landowners said they would sell their woodland if offered 30% more than the market price. However, only 4.20% have previously sold parts of their woodland among the landowners who responded.

Table 2. 3 Descriptive statistics of the Land characteristic variables

Variable		N	Percentage	Mean	Min	Max
Lot Size (acres)		380		62.10	4	1050
Parcel						
	1 parcel	182	47.90%			
	2 parcels	105	27.60%			
	3-5 parcels	88	23.20%			
	More than 10 parcels	5	1.30%			
Ownership						
	Family	157	41.30%			
	Individual	211	55.50%			
	Multiple ownership	12	3.20%			
Acquisition		380				
	Inherited		22.90%			
	Purchased		76.10%			
	Received as a gift		1.10%			
Ownership Length (Years)				44.475	1	221
Residency						
	No	125	32.90%			
	Yes	255	67.10%			
Plan						
	No	310	81.60%			
	Yes	70	18.40%			
Public Land						
	No	354	93.20%			
	Yes	26	6.80%			

Moreover, most of the woodland owners said any new development activity within 10 miles of their land would not persuade them to sell their land. Table 2.4 summarizes the sociodemographic characteristics of the woodland owners.

Table 2.4 Descriptive statistics of the Ownership Plan variables

Variable		**N**	**Percentage**
Offer Received			
	No	197	51.80%
	Yes	183	48.20%
Land Sold			
	No	364	95.80%
	Yes	16	4.20%
Sell at the Equal market price			
	Sell	2	0.50%
	Would not sell	378	99.50%
Sell at a 10% higher price			
	Sell	9	2.40%
	Would not sell	371	97.60%
Sell at a 20% higher price		380	
	Sell	18	4.70%
	Would not sell	362	95.30%
Sell at a 30% higher price			
	Sell	72	18.90%
	Would not sell	308	81.10%
Development Presence			
	Do not know	31	8.20%
	Likely	3	0.80%
	Unlikely	74	19.50%
	Very likely	12	3.20%
	Very Unlikely	260	68.40%

The mean age of the landowners was 64.48 years, and 83.70% were males. Very few (1.80%) landowners had less than a high school level education. About half of the landowners had either college undergraduate degrees (27.10%) or high school diplomas (24.50%). There were about 19% of landowners with graduate degrees.

Table 2.5 Descriptive statistics of the Sociodemographic variables

Variable		N= 380		Mean
Age				64.48
Gender				
	Female	62	16.30%	
	Male	318	83.70%	
Education				
	Less than High School	7	1.80%	
	High School Diploma	93	24.50%	
	Some College/Technical School	73	19.20%	
	Associate degree	33	8.70%	
	College undergraduate	103	27.10%	
	Graduate Degree	71	18.70%	
Income				
	Less than $25000	21	5.50%	
	$25000-50000	41	10.80%	
	$50001-75000	66	17.40%	
	$75001-100000	59	15.50%	
	$100001-125000	43	11.30%	
	$125001-150000	38	10%	
	$150001-175000	28	7.40%	
	More than $175000	84	22.10%	

Most of the landowners were in the higher income category. 22.10% of woodland owners said that their household income was more than $175,000, while only 5.50% of the woodland owners were from households with less than $25,000 annual income. In Table 2.5, the results of ownership motivation questions are summarized. Woodland owners were asked landowners had either college undergraduate degrees (27.10%) or high school diplomas (24.50%). There were about 19% of landowners with graduate degrees. Most of the landowners were in the higher income category. 22.10% of woodland owners said that their household income was more than 175,000$, while only 5.50% of the woodland owners were from households with less than 25,000$ annual income. In Table 2.5, the results of ownership motivation questions are summarized. Woodland owners were asked to rate the ownership motivations from strongly agree to disagree strongly.

Table 2.6 Motivations behind owning woodlands

Motivation	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
Amenity	47.60%	32.40%	15.80%	1.30%	2.90%
Conservation	39.20%	40%	17.40%	1.60%	1.80%
Financial	19.20%	30.50%	34.50%	7.60%	8.20%
Hunting	28.20%	27.60%	26.30%	9.20%	8.70%
Personal Use	26.80%	37.40%	26.60%	5.80%	3.40%
Recreation	24.50%	33.90%	30.50%	5.50%	5.50%
Protect Environment	29.70%	39.50%	25%	3.20%	2.60%
Timber	17.40%	40.80%	28.40%	5.80%	7.60%
Bequest	43.90%	28.40%	22.40%	2.60%	2.60%

Among the woodland owners, 47.60% strongly agreed, and 32.40% agreed that the amenity values were a reason behind owning a woodland. Similarly, 43.90% indicated that they strongly agree with bequest values as ownership motivation. Most woodland owners also agreed that they owned lands because of conservation, timber, personal use of the woodland, and to protect the environment. 34.50% and 30.50% of woodland owners said they were neutral about their lands' financial gains and recreational opportunities, respectively. Overall, woodland owners mostly agreed or were neutral about the ownership motivations on the survey. Only about 8% of the woodland owners strongly disagreed that they own woodland for financial reasons, hunting and for timber production.

Table 2.6 summarizes woodland owners' familiarity with different ecosystem services. Most woodland owners were strongly to moderately familiar with most of the ecosystem services. However, about 28% of the woodland owners said they were unfamiliar with the aesthetic value, carbon sequestration service, and fee-based recreational opportunities of a woodland.

Table 2.7 Familiarity with ecosystem services

Ecosystem Services	**Strongly Familiar**	**Very Familiar**	**Moderately Familiar**	**Slightly familiar**	**Not familiar at all**
Aesthetics	11.10%	18.90%	26.30%	15.30%	28.40%
Biodiversity	12.40%	21.60%	27.60%	15.50%	22.90%
Carbon Sequestration	9.50%	15.50%	24.70%	22.10%	28.20%
Clean Water	17.40%	27.40%	29.20%	12.90%	13.20%
Clean Air	16.10%	30.50%	27.10%	12.40%	13.90%
Personal Recreation	24.20%	33.20%	19.70%	11.30%	11.60%
Fee-based Recreation	8.70%	16.10%	26.10%	21.30%	27.90%
Producing NTFP	10.30%	19.20%	27.40%	22.10%	21.10%
Soil Erosion Control	21.10%	30.50%	26.10%	10.80%	11.60%
Watershed Management	17.90%	27.60%	26.80%	13.20%	14.50%

2.3.2 Logistic regression for modeling private woodland owners' willingness to sell:

Table 2.8 reports the logistic regression analysis results to find the factors associated with landowners' decisions about the sale of woodlands. Most of the landowners indicated that they were not willing to sell woodland at equal the market price to 20% higher than the market price. However, about 19% landowners said they were willing to sell at a higher price. So, The dependent variable of the logistic regression analysis was landowners' willingness to sell lands at 30% higher than the market price. Sociodemographic, Ownership motivation, Ownership plan, Familiarity with ecosystem services variable groups were used as the independent variables in the logistic regression. Forward selection was conducted in R statistical software for model selection using Akaike Information Criteria (AIC) (Core R Team, 2019). The reduced model selected through forward selection had a lower AIC value than the full model. However, analysis of variance test indicated no significant differences between the two models ($p = 0.80$).

Further analysis was conducted using the full model, as the reduced model showed similar predictive performance. Variance inflation factors were calculated for each of the explanatory variables and multicollinearity among explanatory variables were not detected (Ma et al., 2012b). So, the final reduced logistic regression model was

$$
\begin{aligned}
\mathrm{Sell30} = {} & \beta_0 + \beta_1\mathrm{Lotsize} + \beta_2\mathrm{Percel} + \beta_3\mathrm{Acquisition} + \beta_4\mathrm{Owner.Length} + \beta_5\mathrm{Resident} + \beta_6\mathrm{Plan} \\
& + \beta_7\mathrm{Public.Land} + \beta_8\mathrm{Amenity} + \beta_9\mathrm{Conservation} + \beta_{10}\mathrm{Financial} + \beta_{11}\mathrm{Hunting} \\
& + \beta_{12}\mathrm{Personal.Use} + \beta_{13}\mathrm{Recreation} + \beta_{14}\mathrm{Protect.Environment} + \beta_{15}\mathrm{Timber} \\
& + \beta_{16}\mathrm{Bequest} + \beta_{17}\mathrm{Land.Sold} + \beta_{18}\mathrm{Development.Presence} + \beta_{19}\mathrm{Aesthetics} \\
& + \beta_{20}\mathrm{Biodiversity} + \beta_{21}\mathrm{Carbon.sequestration} + \beta_{22}\mathrm{Clean.Water} + \beta_{23}\mathrm{Clean.Air} \\
& + \beta_{24}\mathrm{Personal.recreation} + \beta_{25}\mathrm{Providing.fee.based.ecosystem.services} \\
& + \beta_{26}\mathrm{Production.NTFP} + \beta_{27}\mathrm{Soil.erosion.control} + \beta_{28}\mathrm{Watershed.management} \\
& + \beta_{29}\mathrm{Age} + \beta_{30}\mathrm{Gender} + \beta_{31}\mathrm{Education} + \beta_{32}\mathrm{Income} + \varepsilon
\end{aligned}
$$

Table 2.8 shows logistic regression results on willingness to sell woodlands. Age was negatively significant at 1% level in identifying landowners who intended to sell their woodlands. It implies that older landowners were less likely to sell their woodlands, which is the exact opposite of the woodland conversion decisions observed in Tennessee (Poudyal et al., 2014). Landowners who used the land for recreation were also less likely to sell their woodland as this variable was negatively associated and significant at 1% level. The motivation for owning woodlands for their Amenity values was positively and significantly associated with the intention of selling woodlands. Also, landowners who used their land for hunting were more likely to sell their woodlands. On the other hand, woodland owners who owned land for recreational activities other than hunting were significantly less likely to sell their woodland. Ownership length was also negatively and significantly associated with the intention to sell. Although, it showed that ownership length had no marginal effect on the decision to sell. Overall, these results were consistent with the previous findings (Ma et al., 2012b; Poudyal et al., 2014; Rozance & Rabotyagov, 2014).

Table 2.8 Logistic Regression results to find out the factors associated with woodland owners' decision to sell lands

Variables	**Coefficient (Standard Error)**	**Marginal effect (Standard Error)**
Lot size	0.001(0.002)	-0.01(0.03)
Parcel 2 parcels	-0.275(0.367)	-0.03(0.05)
3-5 parcels	-0.578 (0.419)	-0.06(0.05)
More than 10 parcels	1.127 (1.253)	0.27(0.24)
Ownership Individual	0.046 (0.321)	0.00(0.00)
Multiple ownership	-1.675(1.197)	-0.14 (0.06)
Acquisition-Purchased	-0.243 (0.409)	-0.03 (0.06)
Received as a gift	-13.321(680.6)	-0.22*** (0.05)
Ownership Length	-0.009(0.006)	0.00(0.00)
Resident	-0.569*(0.331)	-0.08(0.05)
Amenity	1.010**(0.503)	0.13* (0.06)
Conservation	-0.601(0.482)	-0.08(0.06)
Financial	-0.319 (0.328)	-0.04(0.04)
Hunting	0.667** (0.339)	0.09(0.04)
Personal Use	0.016(0.371)	0.00(0.05)
Recreation	-1.028***(0.37)	-0.13(0.05)
Protect Environment	0.034(0.393)	0.00(0.05)
Timber	0.376(0.341)	0.05(0.04)
Bequest	-0.463(0.353)	-0.06 (0.06)

continued

Table 2.8 continued

Land Sold	0.962(0.646)	0.15(0.11)
Aesthetics	0.687(0.557)	0.09 (0.07)
Biodiversity	-0.538(0.548)	-0.07 (0.07)
Carbon Sequestration	-0.239(0.436)	-0.03(0.06)
Clean Water	-0.556(0.642)	-0.02(0.08)
Clean Air	-0.114 (0.628)	-0.07(0.08)
Personal Recreation	-0.318(0.369)	-0.04(0.05)
Fee-based ecosystem service	0.382(0.398)	0.05 (0.05)
Production of NTFP	0.322(0.404)	0.04 (0.05)
Soil Erosion Control	-0.463(0.561)	-0.06 (0.07)
Watershed Management	0.277(0.565)	0.04 (0.07)
Age	-0.042***(0.014)	-0.01** (0.00)
Male	-0.175(0.444)	-0.03(0.06)
Education	-0.034(0.314)	0.00(0.04)
Income	-0.121(0.350)	-0.02(0.05)
Constant	2.725**(1.265)	
Observations	380	
Log Likelihood	-155.405	
Akaike Inf. Crit.	380.811	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Along with the logistic regression coefficients, each explanatory variable's marginal effect is also reported in Table 2.8. Marginal effects show the impact on the dependent variable when a unit change in an explanatory variable occurs. For example, changing from being a woodland owner who owns woodland for the amenity values to a woodland owner who does not own land for amenity values results in a 13% decrease in the probability of selling woodlands even when 30% higher than the market price if offered.

Table 2.9 shows the prediction accuracy of the model. Although the model showed good predictive performance (82.63% accuracy), it fails to predict landowners' willingness to sell.

Table 2.9 Predictive performance of the logistic regression model

Actual	Predicted			Prediction accuracy
	Not willing to sell	Willing to sell	Total (380)	82.63%
Not willing to sell	299	9	308	
Willing to sell	57	15	72	

2.4 Discussion:

It is essential to distinguish between woodland owners interested in selling their land and wanting to keep their land in current use. Factors associated with woodland owners' decision to either sell or not sell can help formulate policy targeting specific owner groups.

Logistic regression results for the classification of private woodland owners based on their willingness to sell their woodlands reported in Table 2.8 show that males with college or more education and in the higher income group are less likely to sell their woodlands. However, these results were not statistically significant. Similarly, woodland owners familiar with forest ecosystem services such as biodiversity conservation, carbon sequestration, water quality regulation, air purification, personal recreation, and soil erosion control were less likely to sell their woodlands. However, these results were not also statistically significant. On the other hand, familiarity with forest ecosystem services such as the aesthetic value of a forest, fee-based ecosystem services, and watershed management resulted in a greater probability of selling woodlands. However, these results were statistically insignificant too. Apart from these, woodland owners who owned woodlands for conservation purposes or financial reasons showed a negative relation with the willingness to sell. Again, these relationships were also not statistically significant.

From Table 2.8, Age is negatively and significantly associated with woodland owners' decision to sell their land in Central Ohio. Although, the relatively small marginal effect indicates that unit change in age would result in a significant and minor change in the probability of selling woodlands. However, if the number of younger woodland owners increases, it might lead to more sales of woodlands under development pressures in the region.

Being a resident on the property influenced woodland owners not to sell the woodlands. So, absentee landowners might be more prone to sell their woodlands. Although the number of absentee landowners is relatively smaller in Ohio, they tend to be younger (Gallemore et al., 2018). So, combining the fact that there is a group of young private woodland owners who are non-residents on their property should be a group targeted for forest conservation programs since they are more likely to sell their lands in the current scenario.

Private woodland owners who use their woodlands for amenity values are an essential group when the management of private woodlands is concerned (Kelly et al., 2017). National woodland owner survey reports that owning woodland for amenity values is a major reason for owning woodlands (Butler et al., 2016). Table 2.8 shows that woodland owners who own their woodlands for amenity values were likelier to sell them. Furthermore, in Table 2.6, most of the landowners (around 80%) in this study indicated that amenity values were an ownership motivation for owning lands. Although amenity is positively related to the willingness to sell here, the landowners interested in the amenity are values of their woodlands are more responsive to forest management programs (Schaaf & Broussard, 2006). So, forest management programs that help to improve a forest's amenity values and limit sell, or development of woodlands can be a solution to keep private woodlands in current use.

Like owning woodlands for amenity values, hunting is a prevalent motivation for owning woodlands (Albright et al., 2018; Butler et al., 2021). In Table 2.5, about 55% of people indicated that they owned woodlands for hunting on their land, and Table 2.8 shows that hunting is positively related to the willingness to sell woodlands. The probable reason landowners who are interested in hunting on their land are also interested in selling some of their lands is that those landowners already might have enough land to hunt on even after selling some part of their land. Access to private forests for hunting is continuously declining in the United States, and that would result in increased demand for the sale of public access hunting rights (Kilgore et al., 2008). Therefore, conservation programs that facilitate the sale of hunting licenses could encourage woodland owners to manage their woodlands instead of selling parts of their woodlands.

Table 2.8 also shows that owing woodlands for recreational purposes is negatively associated with the willingness to sell. Although hunting on the land can be considered a recreational activity, in this study, hunting on the land was separated from other recreational activities in the survey. So, private woodland owners who use their land for recreational purposes other than hunting, are less likely to sell their lands. This finding about recreational use of private woodlands matches another study, as recreational use of private forests is higher in older people with more income (Kreye et al., 2019). So, older private woodland owners residing on their property who use their lands for recreational activities create an ownership group. According to this study, this landowner group is less likely to sell their woodlands in central Ohio. On the other hand, private woodland owners who own their land for hunting and amenity values are more likely to sell their lands.

Table 2.9 shows the predictive performance of the model. Although with 82.63% accuracy, the overall prediction performance is good, it performs poorly in classifying landowners who are willing to sell. However, the logistic model can identify the landowners who are not willing to sell with a 97.07% accuracy.

2.5 Conclusion:

This study focused on the factors of Ohio woodland owners' willingness to sell woodlands. Continuous population growth and resulting development pressure can influence private woodland owners to sell their woodlands. These private woodland supply vital ecosystem services in Central Ohio and surrounding counties. The sale and consequent conversion of these private woodlands will damage the natural habitat of multiple species and hamper multiple ecosystem services that are essential for human well-being. So, identifying factors that influence the private woodland owners' decision to sell woodlands can help inform policies that persuade those owners to keep their lands in current management.

This study found that owning woodlands for amenity values, use of woodlands for hunting and other recreational purposes, and the age of the landowners are significant factors in the binary classification of woodland owners based on their willingness to sell. Owning woodlands for hunting and amenities was positively associated with selling intentions. On the other hand, the age of woodland owners, use of woodlands for recreational purposes, and being resident on the property was negatively associated with selling.

Chapter 3: Preferences and Willingness to Enroll in Woodland Conservation Program in Ohio, USA

Abstract:

The projected new developments put the private woodlands in Central Ohio at risk of Conversion in the coming years. Conservation programs can incentivize woodland owners to manage their woodlands to supply ecosystem services and stall changes in land use. Little is understood about Ohio's private woodland owners' willingness to participate and preferred attributes for such programs. This study surveyed private woodland owners in Ohio to elicit the choice preference in a hypothetical conservation program through best-worst choice profiles and binary choice experiments. Woodland owners were asked to select the best and worst attributes of different programs and their willingness to enroll. Best-Worst scores, Conditional logistic, and Random Effects logistic regression were used to explain woodland owners' priorities. Best-Worst scores show that the highest revenue ($100 acre/year) was the most selected attribute in all choice profiles. A non-profit program structure and no withdrawal penalty are most desirable to woodland owners besides revenue at different amounts. Both regression models show that revenue

is significant and positively associated with willingness to participate, and only a withdrawal penalty of $10/acre was not statistically significant. Landowners also chose different program attributes based on their groups. More educated landowners are significantly influenced by revenue, whereas landowners who own more land see management organization as a less important attribute for enrollment decisions. Private woodland owners are willing to sacrifice revenue for their preferred attributes in a program. For example, to go to a 30-year contract from a 60-year contract, woodland owners are willing to take $27.74 acre/year less in revenue. Based on these findings, the above results can be beneficial to policymakers in planning new conservation programs that ensure the supply of crucial ecosystem services through private woodlands in Ohio

3.1 Background and Literature Review:

There has been a global expansion of conserved areas since the 1980s (Zimmerer et al., 2004). However, conservation outside government-protected areas continues to be challenging, especially with urban growth trends in private lands (Brown et al., 2005; Farmer et al., 2016). Private woodlands are essential for the conservation and maintained supply of ecosystems service in the United States since private entities own most (56%) of the forestland (Butler, 2008). Forests, including private woodlands, provide abundant regulating, provisioning, cultural, and supporting ecosystem services in the united states (Fisher & Christopher, 2007; Frey et al., 2021; Warnell et al., 2020). These ecosystem services provide many benefits ranging from human health and natural hazard protection, climate regulation, ensuring fresh water supply, and maintaining long-term food production (Ash et al., 2010). Among private entities, family forest owners or non-industrial private woodland owners control the largest part of the forest lands (62% of the privately owned forest lands) (Butler, 2008). So, the conservation of forests in the United States greatly depends on the participation of private woodland owners.

Ohio has a forest cover of about 8 million acres which covers 30% of the State area (Albright et al., 2018), and private forest landowners own 68% (5.8 million acres) of these forested lands (Widmann et al., 2009). Of the 336,000 private forest landowners in Ohio, 93% own less than 50 acres of land (Widmann et al., 2009). Because private forest owners are the majority, they decide the fate of forest cover in Ohio. How they would manage their forestland is vital for the continued supply of timber and non-timber forest products and services.

The choices private landowners and communities make about using natural resources impact the type, quality, and quantity of services an ecosystem offers (Jacka et al., 2008). From a landowner's perspective, the generation of ecosystem services is an externality, which means they do not get a direct monetary benefit from it (Scherr et al., 2009).To promote conservation and sustainability, payment for ecosystem services (PES) is a system that incorporates both economic and social incentives (Naeem et al., 2015). Usually, the PES program structure requires that the users of environmental or ecosystem services pay for the desired land management practices by the landowners (Pagiola et al., 2005). In the case of the United States, the incentives for the desired land or forest management practices could be funded by various federal and state-sponsored programs (McGinley & Cubbage, 2020). This technique is adopted globally, where the adoption of particular forest management practices is traded with monetary incentives to ensure the supply of ecosystem services (Salzman et al., 2018). For example, payment for forest conservation through a Mexican federal program reduced deforestation by 50% (Alix-Garcia et al., 2012).

Before the 1990s, the need for non-industrial private woodland conservation was understood, and through the 1990 Farm bill, Congress sponsored the Stewardship Incentive Program to improve woodlands in the United States (Bell et al., 1994). Zhang & Flick,(2001), found that government incentive programs influenced woodland owners to adopt forest management practices that they would not usually do under strict regulations. On the other hand, Klosowski et al., (2001), found that increased incentives through tax reduction did not significantly increase the probability of program participation. So, solely incentives would not persuade private woodland owners to enroll in forest management practices and there might be other factors associated with private landowners that might influence their management decisions.

What factors influence private woodland owners to participate in various forest management activities, including timber and non-timber forest products and services generation, is widely studied globally, including in the United States, where many private woodlands exist(Becker et al., 2013; Clarke et al., 2021; Silver et al., 2015). As owners have diverse motivations for owning woodlands, some of them with more than one reason, they will have various influencing factors directing how they manage their woodlands (Bengston et al., 2011). A study of Georgia private woodland owners found that they prefer direct payment over tax credits and needed more payment if the contract length was longer. Also, risk-neutral and risk-seeking woodland owners were less prone to enrolling in such forest conservation programs (Kang et al., 2019b). Another Tennessee study on participation in Forest Stewardship Program found that both forms of direct and indirect incentives promote enrollment in such programs; however, a direct monetary incentive was found to be less influential when compared to knowledge and attitudes towards such programs (Bell et al., 1994). The supply of various forest ecosystems services through forest conservation programs generally have only non-market values, and creating a market for these services through non-market valuation can incentivize the supply of ecosystem services (Salzman, 2005)

Several environmental valuation techniques are classified into stated preference and revealed preference methods for estimation of benefits of public environmental goods. Stated preference methods use a hypothetical scenario to elicit ex-ante willingness to pay or accept environmental services, whereas revealed preference use real choices people make for valuation (Whitehead et al., 2008). The stated preference method of environmental valuation is usually conducted by either Contingent Valuation (CV) or Choice experiments (CE) (Hanley & Czajkowski, 2020).

In the United States, environmental valuation originally started with the travel cost model (a revealed preference method) and other contingent valuation techniques during the 1960s (Hanley et al., 1998). Choice experiments have been an important tool in environmental valuation techniques where stated preference methods use multi-feature choice experiments instead of ranking and rating programs and attributes (Adamowicz et al., 1998). Choice experiments stem from Lancaster's Theory of Value, where he states that the goods do not give utility but rather multiple characteristics of the goods and their combinations give utility (Lancaster, 1966). In unison, this theory of value and random utility theory (Hanley et al., 1998; Manski, 1977; Thurstone, 1927) is the base of choice experiments where choices are made to maximize utility(Louviere et al., 2015). One form of such choice experiment is called Best-Worst scaling. Louviere et al., (2015), devised Best-Worst Scaling (BWS), also known as Maximum Difference Scaling (MaxDiff), which uses selection of profile attributes instead of ranking the whole profile on a scale (Cohen, 2003; Louviere et al., 2015). People make errors when choosing from different options, and with repeated choice tasks, choice frequencies would show how much people value one option compared to another (Louviere et al., 2015; Thurstone, 1927). There are three types of Best-Worst scaling choice experiments. They are called object case (Case-1), profile case (case-2), and multi-profile case (case-3) (Louviere et al., 2015). In profile case (case-2) Best-Worst scaling, it is possible to compare woodland owners' preferences for different program attributes.

Although program requirements are critical in landowner participation in voluntary conservation programs (Knoot et al., 2015), most studies do compare among program requirements. So, how landowners make trade-offs between alternative choices in a conservation program cannot be understood. A study of private landowners in Finland, on their interest in participating in payment for ecosystems services program to enhance amenity values found that forest management and clear-cutting restrictions negatively affect participation (Mäntymaa et al., 2018). However, comparing these two types of restrictions is impossible using the conventional stated preference valuation methods. To see the attribute impacts in environmental valuations, Best-Worst scaling methods can be successfully used (Flynn et al., 2007).

Existing forest conservation programs often fail to reach all eligible family forest owners, and participants of the programs are not different from non-participants in their decision to subdivide land (Butler et al., 2014). These sales or subdivisions of private woodlands can lead to forest fragmentation and adversely impact ecosystem services, thus defeating the purpose of forest conservation programs. So, designing appropriate conservation programs based on landowner preferences is essential. D'Amato et al., (2010), showed that traditional timber management practices were insufficient in covering the increasing property taxes. Forest conservation programs such as the enrollment in conservation easements would be more viable in preventing forest conversion and fragmentation. Conservation programs in the form of easements require a contract between the landowner and a non-governmental or governmental agency that prevents any new development on the land for perpetuity (Ma et al., 2012a). On the other hand, carbon credit programs conserve private forests by using contracts prohibiting land conversion(Funk et al., 2014; Huang & Kronrad, 2001). These carbon credit programs have limited-time contracts and payment schemes incentivizing landowners' enrollment (Miller et al., 2012). However, studies show that aside from revenue generated from such programs, landowners were also concerned about the contract length, management requirements, and withdrawal penalty of these programs (Khanal et al., 2017; Markowski-Lindsay et al., 2011).

The design of effective forest conservation programs that can reach more private woodland owners requires careful consideration of program attributes (M.G. et al., 2013). However, there is a lack of studies that focuses on private woodland owners' preferences for the program attributes in Ohio. The findings of this study will help design effective woodland conservation programs in Ohio.

3.2 Materials and Methods:

3.2.1 Study Area:

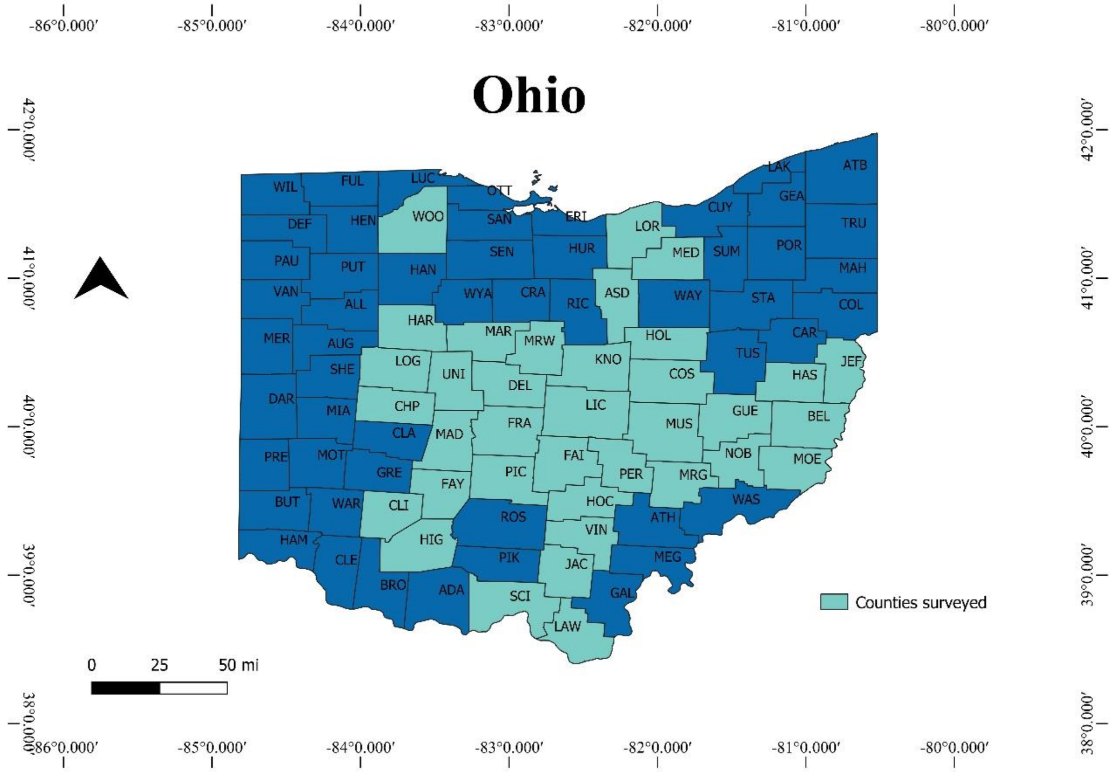

Figure 3.1: Selected counties for the study in Ohio

This study's primary area of interest was the Central-Ohio region and surrounding counties. Additionally, counties near the metropolitan area of Cleveland (Lorain and Medina county) were also surveyed in this study.

3.2.2 Econometric Model:

3.2.2.1 Random Utility Framework:

If among choice alternatives in a choice set X, i is chosen by jth individual, then the utility is given by U_{ij}. This measure of utility has one systematic component V_{ij} and one random component ε_{ij} (Louviere et al., 2000).

So, $U_{ij} = V_{ij} + \varepsilon_{ij}$ (Eq. 3-1)

For any individual j, i will be chosen over any other alternative l, only iff $U_{ij} > U_{il}$

The probability of choosing option i instead of choosing option l is given by

$Prob(i|X) = Prob\{V_{ij} + \varepsilon_{ij} > V_{il} + \varepsilon_{il}$, for all $i, l \in X\}$ (Eq. 3-2)

Which maximizes the utility for the person making a choice (Hanley et al., 1998). Here, the assumption about the error term or the random component is that it follows Gumbel distribution and is IID (independently and identically distributed) (Hanley et al., 1998; McFadden, 1973).

3.2.2.2 Best-Worst Choice Framework:

The previous section discusses how choice is made under a random utility maximization framework where one choice is made to maximize the utility. In this study, we have used the case-2 or profile case Best-Worst scaling where a pair of choices were made from the choice profile and the assumption was that the pair that maximizes the utility difference would be chosen (Flynn et al., 2007)

As described by Louviere et al., 2015, Let's consider a scenario where X is a choice set with a set of attributes $M = \{1,2, \dots m\}$ where $m \geq 2$. Each attribute has more than one attribute level. So, attribute i has $q(i)$ level where $i = 1,2,3, \dots m$. A typical profile j is expressed as x_{ji}, where i has multiple levels. Also, for each attribute i there is a utility coefficient β ($\beta = \beta_1, \dots, \beta_m$)

Suppose choice profile X is now expressed as X_k with multiple attributes, and since each attribute has multiple levels, choice options would be expressed as X_{kr} where $r = 1,2,3 \dots m$. For profile Best-Worst scaling, lest assume that the one attribute x_{ki} is chosen as the best attribute in profile X_k and $x_{ki'}$ is chosen as the worst attribute in profile X_k given that $i \neq i'$. So, $x_{ki'}$ and x_{ki} is a choice pair from profile X_k. This profile chose because the utility difference between these two attributes is greatest and the probability of choosing this pair over any other pair is given by the following equation

$$P_{BW}\,(ii'|X_k) = \frac{exp(\beta_i X_{ki} - \beta_{i'} X_{ki'})}{\sum j \neq j'; j, j' \in M exp\left(\beta_j X_{kj} - \beta_{j'} X_{kj'}\right)}$$

(Eq. 3-3)

3.2.2.3 Random utility representation:

From the previous discussion about the utility maximization framework, the random utility representation of the chosen pair is given by:

$$P_{BW}\,(ii'|X_k) = Pr\left([u(X_{ki}) - u(X_{ki'})] + \varepsilon_{ii'} \geq \left[u\left(X_{kj}\right) - u\left(X_{kj'}\right)\right] + \varepsilon_{jj'}, \forall j, j' \in M,\ j \neq j'\right)$$

$$= \frac{exp - [u(X_{ki}) - u(X_{ki'})]}{\sum j \neq j'; j, j' \in M \, exp - [u(X_{kj}) - u(X_{kj'})]}$$
(Eq. 3-4)

Here, u represents a single latent utility scale (Louviere et al., 2015). Coefficients of conditional logit regression and random effects logit regression will show values on this latent utility scale (Soto & Adams, 2012; White et al., 2018).

3.2.3 Building choice profiles:

According to Louviere et al., 2000, three key criteria need to be fulfilled to model the behavior of individuals. One is that there should be choice sets with alternatives, observed attributes of people making the decisions, and a way to model how people choose among alternatives with a distribution of their behavioral patterns.

To fulfill these criteria and the building of choice tasks, there were two steps in selecting attributes of a hypothetical conservation program that supplies ecosystem services. One is to select how many attributes or features should be considered, and another is how many levels should be in each attribute or feature. By consulting the literature in Table 3.1, the following four attributes were chosen to build choice profiles for Best-Worst scaling tasks.

1. **Organization:** This is about the organization that a woodland owner will work with to participate in the forest conservation program. Three possible entities can run the program.

Table 3.1 Literature used for building choice profiles

Study	Data	Attribute	Levels
(Kang et al., 2019a)	South-East Georgia private forest owners, n= 253	Annual payment	Revenue 10$, 30$, 60$, 80$ acre/year
		Contract length	10, 30, 60 years, and permanent contract length
		Payment mode	Cash, Tax credits
(M. C. Kelly et al., 2015)	New York family forest owners	Time commitment	99, 50, and 30 years contract
(Knoot et al., 2015)	Wisconsin family forest owners	Institutional arrangement	Government and Private
(Mutandwa et al., 2019)	Mississippi private forest owners	Bid amount	$1, $3, $5, $8, $12, $20, $30, $40, $50, $60, $80, $100, $120, $150, and $200
		Contract length	10 years
(Rodriguez et al., 2012)	Endangered species habitat conservation using a survey of North Carolina Farm Bureau county advisory board members	Easement	
		Contract length	1, 5, 10, 15, 20, 25, 30, and 50 years

continued

Table 3.1 continued

(Khanal et al., 2017)	Carbon credit	Contract length	35-40 years
(LeVert et al., 2009)	Willingness to sell	Revenue	$100, $300, $500,$700

They are Government organizations (State/Federal), For-profit organizations, and Non-profit organizations.

2. **Revenue**: Amount of income generated for participating in the program. There are three possible rates of $50, $75, and $100 acre/year revenue a woodland owner can generate for the amount of land they have enrolled in the program.
3. **Contract length:** The amount of time a woodland owner will be under contract for this hypothetical program. The possible contract lengths are 10, 30, and 60 years.
4. **Withdrawal Penalty:** To get out of the program, a woodland owner will have to pay a withdrawal penalty for breaking the contract. The penalties can be $0, $10, and $40 for per acre of land enrolled in the program.

Using these four attributes and three attribute levels for each attribute, it is possible to generate 3^4 or 81 choice questions from which a woodland owner can choose the best and worst attributes. However, using a questionnaire with many questions is not practical because it can easily cause choice fatigue (Louviere et al., 2015).

Worst Feature (Check one)	Forest conservation Program 1	Best Feature (Check one)
☐	A program run by a For-profit organization	☐
☐	You will get $100 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 10 years	☐
☐	Your withdrawal penalty would be $10 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

Figure 3.2: Example of a Best-Worst scaling choice question

On the other hand, if all the possible combinations of attribute levels are not used, each attribute level will not be equally available to choose from the choice questions. A fractional factorial design technique was applied to select a subset of all possible questions to overcome this problem. These type of designs are called orthogonal main effect plans (OMEP), which allows independent estimation of the main effects; however, they cannot show the measure of interaction terms of attributes due to iid (independent and identically distributed) errors (Louviere et al., 2015). Using an R-package called support.BWS2 (Aizaki & Fogarty, 2019), this orthogonal main effect design was generated to select nine best-worst choice questions for the survey. Figure 3.2 shows an example of one of the nine best-worst questions. Each of these questions essentially acts as a profile of a woodland conservation program. Woodland owners were asked to choose one attribute as best and one as worst for each choice question. This part of the choice experiment was task 1. In task 2, woodland owners were asked to judge the combination of the four attributes as a single profile and choose whether they would enroll in that program if the program were available to them. Task 1 was designed to see the effects of each attribute and attribute level on program enrollment, while task 2 could show willingness to accept for attribute level change for a program

3.2.4 Data Collection:

After the survey was designed and approved by the Institutional Review Board (IRB) of The Ohio State University (Study 2021E0614), surveys were deployed through mailing. For the mail survey deployment, a modified Dillman survey method was used (Dillman et al., 2014). First, landowners were notified via a postcard about the survey they would receive. The postcard explained the nature of the research and why the study was necessary. Then first mailings were sent out with a cover letter. The cover letter explained the questionnaire survey's settings and critical terms for a better understanding of the woodland owners. After one month from the first mailing, non-respondents received the survey again. No follow-up postcard was sent to woodland owners who filled out the survey. Records of landowners were collected from property tax rolls, and survey recipients were selected randomly from the records. The landowners who owned at least 4 acres of woodland were chosen for the study. Any written consents were not obtained from the woodland owners. However, filling out the survey and sending it back using business reply envelopes were entirely voluntary. Also, how the identity of the survey participants would be kept anonymous and how the data they entered into the survey would be protected was explained to landowners in the survey instrument. In addition, landowners were also asked to provide their email addresses if they wanted to be contacted for further communications or wanted a summary of the research outcomes using the survey data.

3.2.5 Data Analysis:

As the data were collected using a mail survey method, it required the data to be transferred to an excel file from the paper surveys. After the initial data cleaning in excel, data analysis was conducted using R software (Core R Team, 2019).

Out of 2500 surveys that were sent, 663 people responded with a 26.5% response rate. Among the returned surveys, landowners who did not own any woodlands or owned less than 4 acres of woodland were removed from the analysis. Also, because of the complexity of the best-worst choice question, all the choice questions were not completed in several surveys. This study used 253 surveys with all the choice questions filled out entirely, giving an effective response rate of about 10%. There were some missing values for the Age and Lot size variable. Those missing values were imputed using the random forest regression data imputation technique.

Specifically, data were analyzed using the same R-package (support.BWS2) used to generate the orthogonal main effect plans from which the nine choice questions were developed for the survey. The withdrawal penalty was selected as the base level among the four attributes during the survey design. Moreover, one attribute level was chosen as the base level in the OMEP choice sets for each attribute. Two different analysis techniques were used for task 1 and task 2. In task 1, where landowners were asked to select one attribute as best and one as worst , they essentially selected a pair of attribute levels for each of the nine choice questions. These choice pairs were analyzed using a paired conditional logistic regression model (Flynn et al., 2008). Each choice profile or question has four (n=4) attributes, and they could generate n(n-1) pairs or 12 pairs of best-worst questions. In Table 3.3, there is an example of the 12 best-worst pairs using For profit organization, \$100 revenue, 10 year contract length, and a withdrawal penalty of \$10. Among those 12 possible pairs, the woodland owner would choose the pair that maximizes the utility difference. The following equation adapted from White et al., (2018), shows how utility differences are maximized for each pair.

$$U_{diff}^{i} = \sum_{j=1}^{p} \beta_j^i D_j^i + \sum_{k=1}^{q} \sum_{j=1}^{p} \beta_{jk}^i D_{jk}^i + \varepsilon^i \qquad \text{(Eq. 3-5)}$$

In equation 3-5, the goal is to maximize the utility difference or U_{diff}^{i}. For that, both the attributes and attribute levels were considered. Here, p is the number of attributes, and q

is the number of attribute levels. The number of best-worst combinations is given by $i(i = 1,2, \ldots ,12)$, and j indexes them through each attribute and attribute level. β_j^i are the coefficients of attributes whereas β_{jk}^i are the coefficients of attribute levels. D_j^i denotes the attributes; if an attribute is chosen as best, it takes the value of 1. If the same attribute is chosen as the worst, it takes the value of -1; otherwise, 0 is assigned for that attribute. The same coding scheme is applied to the attribute levels in D_{jk}^i and they are shown in Table 3.3. This coding scheme is called effects coding, which centers the attribute levels on the mean, and it has a significant advantage over other coding schemes like dummy coding (Flynn et al., 2008; Louviere et al., 2015; White et al., 2018).

Among the 12 best-worst pairs, the chosen pair was coded as 1, and all the remaining pairs were coded as 0. This choice was treated as the dependent variable, and all the attribute and attribute levels were the independent variables. For each of the nine questions, different combinations of 12 best-worst pairs were generated. So, a single woodland owner chose nine best-worst pairs among a possible 108 best-worst pairs. The conditional logistic regression model was estimated using each pair's choice as the dependent variable, and all the attributes, and all the attribute and attribute levels were the independent variables. For each of the nine questions, different combinations of 12 best-worst pairs were generated. So, a single woodland owner chose nine best-worst pairs attribute levels, and landowner groups based on the Property size, Gender, Education, Income, and knowledge about Ecosystem services as the independent variables.

Table 3.2 Effects coding for the conditional logit model

Best Level	**Worst Level**	**Organization**	**Revenue**	**Contract Length**	**Withdrawal Penalty**
For Profit	Revenue 100$	1	-1	0	0
For Profit	Contract 10	1	0	-1	0
For Profit	WP 10$	1	0	0	-1
Revenue 100$	For Profit	-1	1	0	0
Revenue 100$	Contract 10	0	1	-1	0
Revenue 100$	WP 10$	0	1	0	-1
Contract 10	For Profit	-1	0	1	0
Contract 10	Revenue 100$	0	-1	1	0
Contract 10	WP 10$	0	0	1	-1
WP 10$	For Profit	-1	0	0	1
WP 10$	Revenue 100$	0	-1	0	1
WP 10$	Contract 10	0	0	-1	1

Random effects logistic regression analysis was used to analyze the data for task 2. The choice of whether a landowner would enroll in a forest conservation program was the dependent variable, and the attribute levels of the programs were used as the dependent variable. Each landowner answered yes or no to nine of these choice scenarios. So, for every landowner, there were nine observations. Random effects logistic regression was used to account for the clustering of these choices. Instead of categorical coding, effects coding was used for the attribute levels. Table 3.3 shows the coding scheme for the random effects logistic regression. Two models were assessed using this task 2 binary choice data. In the first model, all the attribute levels used effects coding. However, in the second model, revenue was quantitatively coded, and using the coefficient of the revenue, willingness to accept for each attribute level was estimated. Also, the revenue trade-off of moving from one attribute level to another was calculated using this revenue coefficient.

Table 3.3 Effects coding for Random Effects Logit model

Attribute	Levels	Effects coding	Effects coding
		For Profit	Government
Organization	For Profit	1	0
	Government	0	1
	Non-profit	-1	-1
Revenue		50$	75$
	50$	1	0
	75$	0	1
	100$	-1	-1
Contract length		10 years	30 years
	10 years	1	0
	30 years	0	1
	60 years	-1	-1
Withdrawal penalty		0$ Penalty	10$ Penalty
	0$ Penalty	1	0
	10$ Penalty	0	1
	40$ Penalty	-1	-1

3.3 Results:

Table 3.4 shows the descriptive statistic of selected variables from the survey aside from the best-worst choice questions. It shows that the responders are primarily older males (82.20% male with a mean age of 62.55 years). Most landowners own less than 100 acres of woodland, and most are single parcel woodlands. Also, these woodlands are either family-owned or there individually owned. Also, most of these woodlands were passed down from the family, as 76.30% of woodland owners stated that they inherited their land. Woodland owners were also asked about their familiarity with different ecosystem services using the l-5 Likert scale, with 5 being extremely familiar. A dummy variable called "Ecosystem" was created using the average Likert scale values to show familiarity with ecosystem services. More than half (55.30%) of woodland owners stated that they were familiar with their lands' different ecosystem services. About half of the landowners were college graduates or had higher degrees, and most of the landowners had income over 100,000$ per year. Also, most of the woodland owners had no written Forest management plan (20.20% of the landowners had a plan), and only 6.70% of woodlands were adjacent to public land. The above results are similar to the 2017-2018 National Woodland Owner Survey (NWOS) (Butler et al., 2021), indicating that the sample used for this study represents the population well.

Table 3.4 Descriptive Statistics woodland owners in choice experiment

Variable	N		Mean	Min	Max
Lot size	253		67.14	4	1050
Parcel					
1 parcel	125	49.40%			
2 parcels	66	26.10%			
3-5 parcels	58	22.90%			
More than 10	4	1.60%			
Ownership					
Family	145	57.30%			
Individual	102	40.30%			
Multiple ownership	6	2.40%			
Acquisition					
Inherited	193	76.30%			
Purchased	56	22.10%			
Received as a gift	4	1.60%			
Ownership Length			42.45	1	221
Residency					
Not-Resident	85	33.60%			
Resident	168	66.40%			
Forest Management Plan					
No	202	79.80%			
Yes	51	20.20%			
Public Land					
No	236	93.30%			
Yes	17	6.70%			
Ecosystem					
No	113	44.70%			
Yes	140	55.30%			
Age	253		62.552	30	93

continued

Table 3.4 continued

Gender		
Female	45	17.80%
Male	208	82.20%
Education		
College or More	131	51.80%
Less than college degree	122	48.20%
Income	253	
Less than 100,000	71	28.10%
More than 100,000	182	71.90%

3.3.1 Best-Worst Scores:

Table 3.5 shows the Best-Worst scores. These results were obtained by counting the approach of Best-Worst choices for each of the nine choice scenarios. Best-Worst scores were calculated by subtracting the number of times one attribute was chosen as worst (W) from the number of times the same attribute was selected as best (B). This table shows that $100 revenue was chosen as the best attribute in a choice profile. It was closely followed by $75 revenue and a $0 withdrawal penalty for early withdrawal from the program. Apart from revenue at different levels, a Non-profit management structure and withdrawal penalty of $10 also showed positive Best-Worst scores. On the other hand, contract lengths of 30 and 60 years were chosen as the worst attributes the most times. Landowners also showed less preference for Government and For-profit management structures, resulting in negative Best-Worst scores. A similar aversion was demonstrated for a significant withdrawal penalty ($40). Table 3.5 also shows that revenue at different levels was chosen as the worst feature in a choice profile several times. This indicates that landowners are not always revenue maximizers; based on their ownership objectives, they are utility maximizers.

Table 3.5: Best-Worst Scores from counting method

Attribute levels	**B**	**W**	**BW**	**stdBW**
Government	47	221	-174	-0.22925
ForProfit	50	274	-224	-0.29513
NonProfit	146	67	79	0.10408
revenue50	376	88	288	0.37945
revenue75	454	13	441	0.58103
revenue100	662	4	658	0.86693
Contract10	89	137	-48	-0.06324
Contract30	13	484	-471	-0.62055
Contract60	19	610	-591	-0.77866
WP0	321	18	303	0.39921
WP10	82	74	8	0.01054
WP40	18	287	-269	-0.35441

B = Number of times chosen as best, W= Number of times chosen as worst,
BW= B-W, stdBW = Standardized BW score

3.3.2 Conditional Logit Analysis Results for attribute and attribute level impacts:

Section 3.3.2 presents conditional logistic regression results for the best-worst data. The results are presented in two tables. Choice tasks had two components, one is the four attributes, and the others are the three attribute levels for each attribute. Table 3.6 shows the attribute level impacts for all the 12 attribute levels, and Table 3.7 presents the coefficients of the program attributes and their interactions with the woodland owner groups. Among the attributes, Table 3.7 shows that revenue and contract length are significant at the 1% level from the conditional logit analysis. Withdrawal penalty was used as the base level for comparing other attributes. Table 3.6 shows the attribute level values. Except for the withdrawal penalty of $10, all the attribute level length of 10 years, and $0 withdrawal penalty more than other attribute levels values were significant at the 1% level. Woodland owners choose $100 revenue, contract These levels have positive coefficients, with the highest value of 1.258 among the significant attribute levels. Among the organization attribute levels, program management by government (-1.278) entities showed negative values in the latent utility scale. Similar negative values are seen in Table 3.7 for revenue of $50 (-1.039) and $75 (-0.219). Except for the $0 withdrawal penalty and contract length of 10 years, all the attribute levels for contract length and withdrawal penalty showed negative coefficients. It indicates that woodland owners prefer the lowest level of contract length of 10 years (1.444) compared to 30 (-0.387) and

60 (-1.066) years of contract length. Among the 3 attribute levels of withdrawal penalty, woodland owners preferred no withdrawal penalty (1.348) in the program structure and showed positive coefficient values. The other two attribute levels of withdrawal penalty (withdrawal penalty of $10 and $40) showed that they are on the negative side of the latent utility scale with coefficient values of -0.092 and - 1.256, respectively.

Table 3.6 shows the attribute level impacts, whereas Table 3.7 shows the attribute impacts as a whole and landowner group interactions with the attributes. Here, the withdrawal penalty was used as the base level for comparison. In Table 3.7, revenue and contract length were significant at the 1% level. However, the effect of the organization was not statistically significant. Revenue was the most preferred attribute, with the withdrawal penalty coming in second. Both the organization and contract length were preferred less by the woodland owners. The amount of woodland a landowner owned significantly impacted their choice of organization. Landowners who owned more woodlands preferred a program's organization attribute less than other program attributes. On the other hand, landowners who were more educated (had a college degree or more education) were significantly attracted by a program's revenue attribute compared to the landowners who had less education. Gender, familiarity with ecosystem services, and income did not significantly relate to the program attributes.

Table 3.7 Attribute impacts and effect of landowner groups on enrollment

Attributes	**Coefficients**
Withdrawal Penalty	0 (base level)
Organization	-0.152 (0.162)
Revenue	1.695*** (0.159)
Contract length	-1.167*** (0.160)
Organization*Ecosystem	0.121 (0.106)
Revenue*Ecosystem	-0.151 (0.102)
Contract_length*Ecosystem	0.073 (0.105)
Organization*Gender	-0.221 (0.139)
Revenue*Gender	-0.206 (0.136)
Contract_length*Gender	-0.100 (0.137)
Organization*Education	-0.167 (0.107)
Revenue*Education	0.179* (0.104)
Contract_length*Education	-0.135 (0.107)
Organization*Lotsize	-0.001*** (0.001)
Revenue*Lotsize	-0.0002 (0.0004)
Contract_length*Lotsize	-0.0005 (0.001)
Organization*Income	-0.054 (0.119)
Revenue*Income	-0.032 (0.115)
Contract_length*Income	-0.017 (0.118)
Observations	27,324
R2	0.145
Max. Possible R2	0.339
Log Likelihood	-3,507.000
Wald Test	2098.000*** (df = 26)
LR Test	4286.000*** (df = 26)
Score (Logrank) Test	3348.000*** (df = 26)

*p<0.1; **p<0.05; ***p<0.01
standard errors are shown in the bracket

3.3.3 Random Effects Logit Analysis for estimation of willingness to accept for program attributes:

Table 3.8 shows the results from the random effects logistic regression of the choice data. In task 2 of the choice experiment questions, landowners were asked if they would participate in a forest conservation program with the same combination of attributes of each of the nine questions. The binary coded responses of the woodland owners and attribute level values were used to estimate the random effects logistic regression model. Table 3.8 shows the results from the random effects logistic regression model in two columns. Model 1 shows the coefficients of attribute levels where effect coding was used.

On the other hand, in model 2, revenue was quantitatively coded, and the coefficient value of revenue (0.046) was used to estimate willingness to accept for attribute levels. Model 1 shows that except for $75 revenue, all the other attribute levels are statistically significant. Non-profit and government organizations positively impact landowners' choice of a forest conservation program. In contrast, a for-profit organization would dissuade a landowner from enrolling in a program. The lowest level of revenue ($50 acre/year) negatively affects the landowner's choice, but the other two levels ($75 and $100 acre/year) have a positive impact. Furthermore, the highest level of revenue has the highest impact on landowners' choices. A short contract length (10 years) and a $0 withdrawal penalty positively and significantly attract landowners to enroll in a program.

However, more extended contracts and a larger withdrawal penalty would discourage landowners from enrolling in a program. Model 2 also shows similar results in terms of the sign of the coefficients but with a slightly smaller magnitude.

Table 3.8 Random Effects Logit Model for willingness to accept estimation

Feature levels	Model 1 (All effect coded)	Model 2 (Revenue quant)
Organization-For-profit	-3.047*** (0.559)	-0.118 (0.208)
Organization-Government	2.862*** (0.360)	0.032 (0.149)
Organization-Non-profit	0.185^{c}	0.086^{c}
Revenue $50	-3.800*** (0.509)	
Revenue $75	0.092 (0.435)	
Revenue $100	3.78^{c}	
Revenue		0.046*** (0.006)
Contract 10	3.355*** (0.357)	1.944*** (0.167)
Contract 30	-1.125** (0.449)	-0.359** (0.167)
Contract 60	-2.21^{c}	-1.635^{c}
Withdrawal 0	1.753***(0.423)	0.869*** (0.152)
Withdrawal 10	1.021*** (0.344)	0.326** (0.163)
Withdrawal 40	-2.774^{c}	-1.195^{c}
Constant	-4.513*** (0.464)	-5.628*** (0.492)
Observations	2,187	2,187
Log Likelihood	-852.912	-953.910
Akaike Inf. Crit.	1,813.824	1,995.820
Bayesian Inf. Crit.	2,121.100	2,246.192

*p<0.1, **p<0.05; ***p<0.01, c is the negative sum of effect coded variables

Standard errors are shown in the bracket

The willingness to accept for each attribute was calculated using model 2. Figure 3.4 shows the willingness to accept for each attribute level. On the X-axis, it shows a willingness to accept values in US dollars, and on the Y-axis, it shows the attribute levels. The negative values of the willingness to accept in Figure 3.4 indicate that the woodland owners would require that additional amount for accepting that attribute level. The highest level of penalty ($40) and the highest level of contract length (60 years) have large values for willingness to accept. On the other hand, positive values indicate that woodland owners would forgo this value in revenue if that attribute level were present in a program. For example, woodland owners preferred a shorter contract length, and they would accept about $42 less in revenue if a shorter contract length (10 years) were offered. These results are further used to calculate the trade-offs for accepting one attribute level over another.

Table 3.9 shows that going from a For-profit organization managing the forest conservation program to a Government organization managing the program would require $3.26 acre/year less payment. On the other hand, if the organization is changed from Non-profit to Government, it would require $1.17 acre/year more payment for enrolling in the program. Woodland owners preferred a smaller contract length, and going from 30 year to a 10 year contract length would result in a $50.06 acre/year decrease in willingness to accept. However, going from a 60 year contract length to a 30 year contract length would require only a $27.74 decrease in willingness to accept.

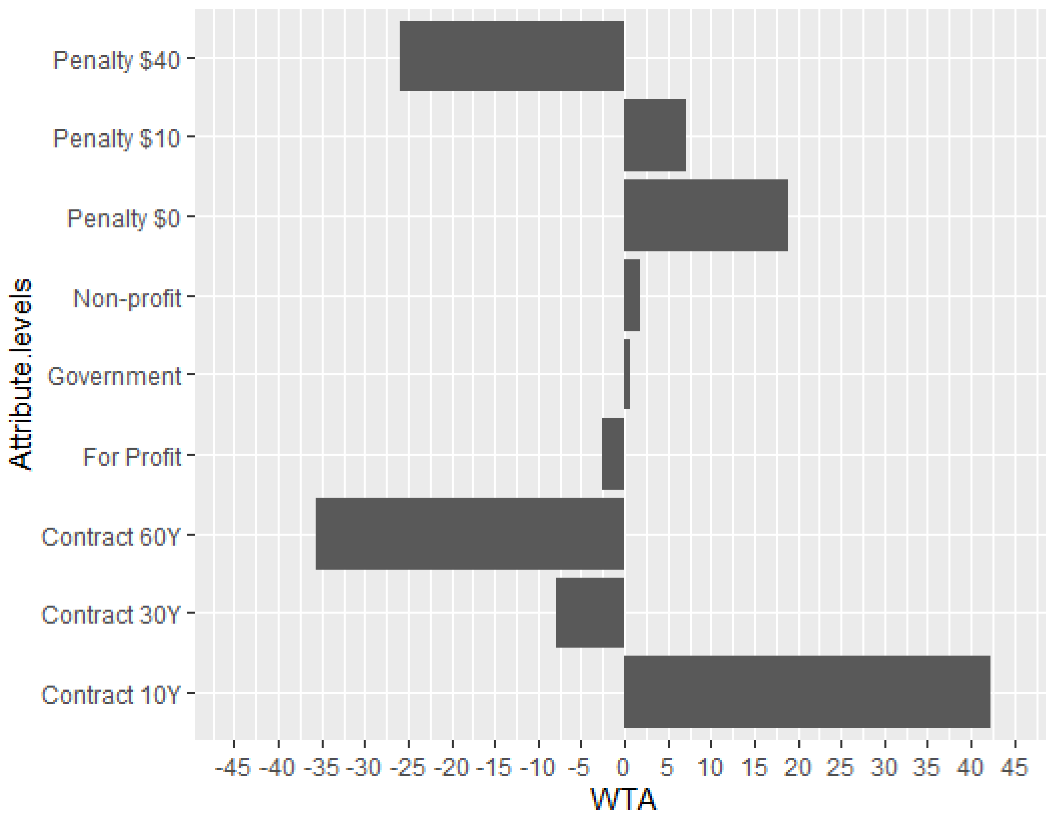

Figure 3.4: Willingness to accept for attribute level

Although the difference in contract length is greater in going from 60 to 30 year contract length, the 10 year contract length was more desirable to the landowners. On the other hand, going from a $40 to $10 withdrawal penalty, landowners are willing to forgo $33.07 acre/year revenue. However, going from a $10 to $0 withdrawal penalty would require only $11.80 acre/year less revenue.

Table 3.9 Willingness to accept (WTA) for attribute level change from Table 3.8

Attribute level change	WTA
For Profit to Government	$3.26
Non-profit to Government	$1.17
Contract 30 years to Contract 10 years	$50.06
Contract 60 years to Contract 30 years	$27.74
Withdrawal Penalty $10 to Withdrawal Penalty $0	$11.80
Withdrawal Penalty $40 to Withdrawal Penalty $10	$33.07

3.4 Discussion:

There is evidence of public support for the supply of ecosystem services from private woodlands (Kreye et al., 2019). So, managing and conserving private woodlands for the continued supply of ecosystem services is indispensable. The findings of this study shed light on multiple essential aspects of designing effective forest conservation programs that can help to maintain a continued supply of public benefits from private woodlands in Ohio.

This study's findings are similar to those of White et al., (2018) and Soto et al., (2016), who applied the same Best-Worst scaling approach. However, they used this method to assess the willingness to enroll in carbon credit programs in the Eastern United States, and different revenue amounts were used in their studies. Because of that, the willingness to accept estimates for different program attributes are different in this study.

However, findings of their studies are consistent with woodland owners' choices about the organization, contract length, revenue, and withdrawal penalty of this study. Other studies also found similar results for the attributes and attribute levels used in this study. Kreye et al., (2017) found that cattle ranchers preferred a contract length of 5 years for enrolling in a voluntary panther conservation program in Florida which was the shortest contract length available for choosing. They also preferred an annual payment like the Ohio woodland owners. Another study of an incentive program for biodiversity conservation found that the highest level of compensation and the lowest level of contract length was more significant for the Southern United States. The willingness to accept attribute values differed because of different program structures (M.G. et al., 2013).

Table 3.5 shows that revenue was chosen as the best attribute most of the time. Landowners chose $100 acre/year (highest revenue level) more times than other levels. Attribute impacts from conditional logistic regression results show that while organization and contract length were on the negative side of the latent utility scale, revenue was more preferred by the landowner in enrolling forest conservation programs. This finding is consistent with similar studies on forest conservation programs (Kang et al., 2019a; Soto et al., 2016; White et al., 2018).

Private woodland owners also showed their clear preference for enrolling in a forest conservation program that was not managed by either a government or a for-profit organization. Best-Worst scores in Table 3.5 show that the landowners were more drawn toward non-profit organizations managing forest conservation programs than for-profit or government organizations. Although abundant federal and state programs are available to help private woodland owners manage their woodlands (Best & Wayburn, 2013), landowners still prefer a non-profit entity to manage forest conservation programs. A similar attitude is also seen among the general public about their policy preference regarding private forest management. The general public favors empowerment policy tools which include incentives, learning, and capacity building, compared to authority policy tools comprising regulations and sanctions along with incentives (Schaaf & Broussard, 2006). This dislike for regulations and sanctions that comes with various federal and state programs might be one of the reasons that Ohio woodland owners preferred non-profit management structures for a forest conservation program. As there are public preferences for empowerment policy tools, the possibility of public investment in funding private woodland conservation programs in Ohio should be explored in future research. Private woodland owners also showed their strong preference for revenue by selecting $100 revenues as the best attribute the highest number of times, as reported in Table 3.5.

Table 3.5 shows that private woodland owners choose the shortest contract length of 10 years as the best attribute most of the time compared to 30 or 60 year contracts. Moreover, they chose contract length as the worst attribute for the most time of the nine choice profiles. Similarly, Table 3.7 reports that contract length is negatively associated with the willingness to enroll in a forest conservation program. These findings are consistent with other studies on private woodland owners' participation in forest conservation programs. Kang et al., (2019a), found that with the increase in contract length, the likelihood of participation in payment for ecosystem services decreases in southeast Georgia.

Similarly, long-term contracts and permanent easements dissuade private woodland owners from participating in conservation activities (M.G. et al., 2013). Although longer contract lengths are generally unfavorable among private woodland owners, this study shows that woodland owners would trade off revenue with longer contract lengths if they are compensated accordingly. For example, to go to a 30 year contract from a 10 year contract would require $50.06 acre/year more in revenue.

Private woodland owners also preferred a $0/acre withdrawal penalty for breaching the contract. Conditional logistic regression results reported in Table 3.6 shows that landowners did not prefer withdrawal penalties of $10/acre or $40/acre since the coefficients of the conditional logistic regression show that they are on the negative side of the latent utility scale. Although some studies found that withdrawal penalties are positively associated with enrollment in forest conservative programs (Frey et al., 2019), other studies found that significant withdrawal penalties can work as a deterrent in participating in forest conservation programs (Fletcher et al., 2009; Ma et al., 2014). Moreover, this study found that private woodland owners are willing to trade off between different levels of withdrawal penalty. For example, to go to a $0/acre withdrawal penalty from a $10/acre one, woodland owners are willing to let go of $11.80 acre/year in revenue. This trade-off indicates that private woodland owners prefer a less restrictive forest conservation program.

Also, different landowner groups showed their preference for different attribute levels. Private woodland owners who owned more lands disregarded the organization as an attribute when choosing the best and worst attributes from choice profiles. So, they were more concerned about the revenue, contract length, and withdrawal penalty. Level of education also had an impact on landowners' preferences. More educated landowners significantly preferred the revenue attribute while choosing from program attributes. Additionally, gender, familiarity with ecosystem services, and income did not influence landowners' decision to choose the best and worst attribute levels for each choice profile.

The results of this study apply to counties surveyed in Ohio. Further study is required to generalize for the state and incorporate these findings in conservation programs, including all Ohio counties.

3.5 Conclusion:

This study analyzed Ohio woodland owners' preferences through the Best-Worst scaling choice experiment. It showed that woodland owners are willing to enroll in forest conservation programs that supply critical ecosystem services in Central Ohio and its surrounding counties. Private woodlands are essential for maintaining ecosystem services, as most of the forests in Ohio are owned by these woodland owners in the region. So, their willingness to participate in such programs can lead to forest conservation programs focusing on the supply of ecosystem services.

Among different attributes and attribute levels, woodland owners preferred the potential revenue generated from participating in the program compared to other attributes. They also preferred to work with non-profit organizations. Private woodland owners also showed strong interest in conservation programs with shorter contract lengths and smaller withdrawal penalties. Education level and woodland size also influenced their choice of program attributes. Landowners with larger woodlands found that program managing organization was less important when deciding to enroll. More educated landowners found revenue was a more important attribute of a conservation program. This study also quantified the willingness to accept for each attribute level of a conservation program. Enrollment in programs with higher withdrawal penalties and longer contract length required significantly larger revenue from the program. At the same time, landowners would accept less payments if non-profit organizations managed the program and the contract length was shorter. Overall, these findings can be used to design more appropriate forest conservation programs that attract greater participation of private woodland owners in Ohio.

Chapter 4: Conclusion and Limitations

The focus of this research was to study private woodland owners from two angles. Firstly, to see their interest in selling woodland when offered higher prices than the current market. Secondly, their interest in participating in forest conservation programs that mitigate the adverse effects that usually come from the sale of private woodland in the form of ecosystem service loss from land conversions.

This study focused on private woodland owners in Central Ohio and surrounding counties since the projected development activities are centered in these areas. The first study examined the contributing factors to woodland owners' decision to sell woodland under different price scenarios. Around 19% of woodland owners indicated that they would sell their woodlands if they were offered 30% more than the market price for their woodlands. Although this suggests that a relatively low number of woodland owners are interested in selling their woodlands, the continuously increasing development pressure would attract more landowners to sell their woodlands. Age and ownership length

The second study looked at the preference of woodland owners for forest conservation programs. Private woodland owners showed their interest in enrolling in forest conservation programs. More specifically, their preferences in the varying attributes of such programs. Woodland owners indicated a strong preference for monetary incentives, reporting similar findings for Ohio (Farmer et al., 2015). They also showed their strong preferences for other program attributes too. Landowners indicated they would like to work with non-profit entities and are less interested in working with federal/state agencies. They also preferred a shorter contract length and smaller withdrawal penalties for removing their lands from the contract. Different landowner groups also preferred different program attributes. Landowners with larger lands were less concerned about the organization managing the forest conservation program. On the other hand, more educated landowners chose the revenue attribute more times.

One of the significant limitations of this study was that all the counties of Ohio were not a part of the study. So, findings from these two studies cannot be generalized for recommending policy for the whole state. However, designing a regional private woodland conservation strategy for Central Ohio can be aided by the results of these studies. Moreover, landowners were not contacted before developing the program attributes and attribute levels. A preliminary survey or interviews with woodland owners could help explore program attributes that were more important to the woodland owners. Addressing these limitations in future research could help to better understand woodland owners' decision to sell and their preferences.

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Appendix A. Survey Instrument

THE OHIO STATE UNIVERSITY
COLLEGE OF FOOD, AGRICULTURAL, AND ENVIRONMENTAL SCIENCES

<Code>

Dear woodland owner,

We are conducting a survey of woodland owners in Ohio to learn about your interest in implementing conservation practices on your woodland to generate natural resource benefits. You were randomly selected from property tax rolls in the county in which your woodland is located.

These natural resource benefits are also known as **ecosystem services**. These benefits include a wide range of goods, services, and benefits that people obtain from natural resources such as your woodland. Some of these services could be, but not limited to, cleaning of air by producing oxygen and purifying it, keeping the water clean by decreasing soil and chemical runoff to nearby rivers, streams, lakes, and ponds. Woodlands can improve the visual appearance or aesthetics of the surrounding landscapes. The presence of woodlands can serve as aquifer recharge areas, which decreases the chances of drought and flood in the area. So, they provide essential watershed management services. Trees and plants in woodlands capture and store carbon dioxide from the atmosphere through the carbon sequestration process. Woodlands also improves biodiversity by providing habitat for many game and non-game wildlife species.

First, this survey will inquire about woodland owners' preference for selling their land at different price scenarios. Next, this survey aims to determine woodland owner awareness and interest in supplying ecosystem services by participating in forest conservation programs. Combining the survey results will identify the factors that should be considered to raise woodland owners' awareness and interest in participating in conservation practices to generate these ecosystem services.

We stress that all of your answers will remain strictly confidential. The data will only be analyzed in aggregate and will be completely anonymous. No information about individual identity, views, or usage patterns will be provided to any other agency or person. All survey responses will be destroyed after the data analysis is completed. Your de-identified information may be shared with other researchers without additional informed consent for data analysis purposes. Participation is voluntary, and responses will remain completely confidential. Your name and contact information will never in any way be released or associated with your answers in reporting the data. In addition, there are no known risks or direct personal benefits associated with participation in this study. For questions about your rights as a participant in this study or to discuss other study-related concerns or complaints with someone who is not part of the research team, you may contact The Office of Responsible Research Practices at 1-614-688-4792 or hsconcerns@osu.edu.

We understand that it will take some of your valuable time to complete this survey. If you would like a copy of the study when completed, please indicate so at the end of this survey. We will be happy to provide you with copies of writings based on this study. Thank you in advance for your cooperation and contribution to this study.
If you have any questions regarding the survey, please feel free to contact Dr. Sayeed Mehmood at mehmood.9@osu.edu. Thank you very much for your help with this important study.

Part 1: We would like to learn about the woodland that you own.

1. Do you own woodland?
☐ No (If you answered no, please seal this questionnaire and return it to us, and we will not bother you with unnecessary reminder letters. Thank you for your time.)
☐ Yes ___ Acres_________________________ County. Property Zip code _____

2. How many unconnected parcels or tracts of forestland do you own?
☐ 1 parcel ☐ 2 parcels ☐ 3-5 parcels ☐ 6-10 parcels ☐ More than 10 parcels

3. Which category below best describes your ownership? (Select only one)
☐ Individual ☐ Family ☐ Multiple ownership

4. How did you acquire your woodland?
☐ Purchased ☐ Inherited ☐ Received as a gift. ☐ Other **(Please specify) _______**

5. How long have you or your family owned this land? (Enter **NUMBER** of years; if you own multiple tracts, please enter the length of ownership for the tract that you have owned the **longest**)
☐ _______ **(Number of Years)**

6. Is your primary residence located at the **same property** as your **woodlands**?
☐ Yes ☐ No, I live ________ miles from my woodland property.

7. If you have answered **"No"** to the previous question, how many times do you visit your woodland on average **in a year**? ☐ _______ **(Number of visits)**

8. Do you have a written management plan for your woodland?
☐ Yes, Forest plan ☐ No ☐ I am not sure.

9. Is your property adjacent to public lands?
☐ Yes ☐ No

10. How important are the following reasons for owning your woodland? Check only one box for each ownership reason?

	Importance				
Reasons for owning woodland	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Amenity (Includes beauty, scenery, privacy, raise a family)	☐	☐	☐	☐	☐
Conservation (Includes protecting nature, diversity, water, wildlife)	☐	☐	☐	☐	☐
Financial (Includes owning land for investment)	☐	☐	☐	☐	☐

Hunting (Includes owning land to hunt)	□	□	□	□	□
Personal use of wood (Includes using wood from land)	□	□	□	□	□
Recreation other than hunting (Includes using land for recreational activities other than hunting)	□	□	□	□	□
Protect environment (water, air, and others)	□	□	□	□	□
Timber (Includes owning land to manage for timber)	□	□	□	□	□
Pass land on to my children or other heirs	□	□	□	□	□
Others (Please specify) ______________________________	□	□	□	□	□

Part 2: We would like to learn about your plans with your woodland in this section.

11. Would you sell your woodland if you get an offer for your woodland at the current market prices? (Check only **one box**)

□ Very Unlikely □ Unlikely □ Don't know □ Likely □ Very likely

12. Have you received any offers to sell your woodland or parts of your woodland in the last 5 years?

□ Yes □ No

13. Did you sell your woodland or parts of your woodland within the last 5 years?

□ Yes → **If you answered "YES" then what was the main reason for selling your woodland?**

□ No

□ Financial return □ High property tax

□ I didn't have time/ability to manage

□ Other (Please specify)

14. Suppose that a Commercial Real Estate Development Company has approached you with an offer to purchase your woodland. In the following table, each row represents a price level that the hypothetical company might offer. Please indicate your preference for whether you will sell your woodland by checking a box for each of these hypothetical prices. (CHECK **ONE** BOX FOR **EACH ROW**)

Price levels	Sell	Would not sell
Equal to the Current market price for your woodland	□	□
Offered price is 10% higher than the current price	□	□
Offered price is 20% more than the current price	□	□
Offered price is 30% more than the current price	□	□

15. If there are new commercial development projects near (within 1 to 10 miles) your woodland, however, your land price has not changed, how likely are you going to sell your woodland because of the new development?

□ Very Unlikely □ Unlikely □ Don't know □ Likely □ Very likely

Part 3: We would like to learn about your familiarity with ecosystem services.

16. How familiar are you with the following ecosystem services? (CHECK **ONE BOX** FOR **EACH ROW**)

Ecosystem Services	Extremely familiar	Very familiar	Moderately familiar	Slightly familiar	Not familiar at all
Aesthetics	□	□	□	□	□
Biodiversity (Increase richness of plant and animal species)	□	□	□	□	□
Carbon sequestration	□	□	□	□	□
Clean water	□	□	□	□	□
Clean air	□	□	□	□	□
Personal recreation (e.g., hunting, fishing, camping, wildlife watching	□	□	□	□	□
Providing fee-based recreation (e.g., hunting leases, ecotourism)	□	□	□	□	□
Production of non-timber forest products (e.g., maple syrup)	□	□	□	□	□
Soil erosion control	□	□	□	□	□
Watershed management	□	□	□	□	□
Others (Please specify) ___________________________________	□	□	□	□	□

Part 4: We would like to know if you are interested in managing your woodland for supplying ecosystem services in exchange for an annual payment. Information presented below about the hypothetical program features is vital for answering questions following the information.

Suppose you own a hypothetical woodland of 10 acres. A forest conservation program can generate revenue from your woodland if you enroll in the program. There are 4 features of the program, each feature with 3 possible different levels. The 4 features are-

5. **Organization:** This about the organization you would work with to run the forest conservation program. Three possible entities can run the program. They are Government organizations (State/Federal), For-profit organizations, and Non-profit organizations.
6. **Revenue**: You would generate revenue for enrolling in the program. There are 3 possible rates of 50$, 75$, and 100$ acre/year revenue you can generate from the program.
7. **Contract length:** The amount of time you would be under contract for this hypothetical program. The possible contract lengths are 10, 30, and 60 years
8. **Withdrawal Penalty:** If you want to get out of the program, you will pay a withdrawal penalty for breaking the contract. The penalties can be 0$, 10$, and 40$ per acre of land enrolled in the program.

<u>What would you have to do to be part of a forest conservation program?</u>

- You can keep your land in the Current Use program

- To stay in the program, you will have a written forest management plan, and according to the plan, you would manage your woodland for supplying ecosystem services.
- A forester will verify each year that you are complying with the program.
- You will not be able to sell or develop your woodland while you are in-contract.
- If you want to withdraw your woodland from the program, there will be withdrawal penalties specified above.

<u>What do you get from the program?</u>

- If you participate in the program, you will generate additional income for managing your woodland.
- You will supply essential ecosystem services

Instructions: Now, consider each of the following hypothetical forest management programs. Consider all the program features for each program, and please mark **ONLY ONE** worst feature and **ONLY ONE** best feature of the program. The worst feature should be the program feature you like the least, while the best feature should be the one you want most of all. A combination of four features makes a program. There nine such combinations in total.

Consider each Forest management program **ON ITS OWN** when you decide if you would enroll in it if it were available to you. You can check "yes" for more than one program. Before you start answering Q4 .1 to Q4.9, please see the example below to see how to select **ONLY ONE** worst attribute and **ONLY ONE** best attribute of the program

17.

18.
19.

21.
22.

Worst Feature (Check one)	**Example Program**	**Best Feature (Check one)**
☐	Feature #1	✓
☐	Feature #2	☐
✓	Feature #3	☐
☐	Feature #4	☐
Would you enroll in this program if it were available to you? (check one)		
✓ Yes ☐ No		

In the Example Program, there is a tick mark on the **right side** of **feature #1** as this is thought to be the **best feature** and a **tick mark** on **the left side** of the **feature #3** says it is chosen as the **worst feature**. **Combination** of the four features (Example Program) is chosen, so, there is a tick mark beside "Yes"

Worst Feature (Check one)	Forest conservation Program 1	**Best Feature (Check one)**
☐	A program run by a For-profit organization	☐
☐	You will get $100 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 10 years	☐
☐	Your withdrawal penalty would be $10 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

18.

Worst Feature (Check one)	Forest conservation Program 2	Best Feature (Check one)
☐	A program run by a For-profit organization	☐
☐	You will get $75 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 30 years	☐
☐	Your withdrawal penalty would be $0 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

19.

Worst Feature (Check one)	Forest conservation Program 3	Best Feature (Check one)
☐	A program run by a For-profit organization	☐
☐	You will get $50acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 60 years	☐
☐	Your withdrawal penalty would be $40 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

21.

Worst Feature (Check one)	Forest conservation Program 4	Best Feature (Check one)
☐	A program run by a Government organization	☐
☐	You will get $50acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 10 years	☐
☐	Your withdrawal penalty would be $0 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

22.

Worst Feature (Check one)	Forest conservation Program 5	Best Feature (Check one)
☐	A program run by a Non-profit organization	☐
☐	You will get $75 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 10 years	☐
☐	Your withdrawal penalty would be $40 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

23.

Worst Feature (Check one)	Forest conservation Program 6	Best Feature (Check one)
☐	A program run by a Government organization	☐
☐	You will get $75 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 60 years	☐
☐	Your withdrawal penalty would be $10 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

24.

Worst Feature (Check one)	Forest conservation Program 7	Best Feature (Check one)
☐	A program run by a Non-profit organization	☐
☐	You will get $50 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 30 years	☐
☐	Your withdrawal penalty would be $10 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

25.

Worst Feature (Check one)	Forest conservation Program 8	Best Feature (Check one)
☐	A program run by a Non-profit organization	☐
☐	You will get $100 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 60 years	☐
☐	Your withdrawal penalty would be $0 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

26.

Worst Feature (Check one)	Forest conservation Program 9	Best Feature (Check one)
☐	A program run by a Government organization	☐
☐	You will get $100 acre/year as revenue for enrolling in the program	☐
☐	Your Contract length would be 30 years	☐
☐	Your withdrawal penalty would be $40 acre/year	☐
Would you enroll in this program if it were available to you? (check one)		
☐ Yes ☐ No		

Part 5: We would like to learn a little about you.

27. What is your age? _____ years

28. What is your gender? □ Male □ Female

29. What is the highest level of formal education you have completed? ***(Check one)***

□ Less than high school
□ High school diploma / G.E.D.
□ Some college or technical school
□ Associate degree
□ College undergraduate degree (e.g., B.A., B.S.)
□ Graduate degree (e.g., M.S., Ph.D., M.D.)

30. Which of the following best describes your total 2019 annual household income before taxes?

□ Less than 25,000
□ 25,001 – 50,000
□ 50,001 – 75,000
□ 75,001 – 100,000
□ 100,001 – 125,000
□ 125,001 – 150,000
□ 150,001 – 175,000
□ More than 175,000

What percentage of your income comes from your woodland?

□ 25% or less □ 26 -50% □ 51-75% □ Over 75%

None of the information that you provide will be disclosed. We do not associate your name with the information you provide. However, it would be extremely valuable to the project in studying the potential of supplying ecosystem services if we can contact a sample of forest owners for further analysis based on the responses to this survey. Would you be willing to be contacted by researchers if selected?

□Yes □ No

If you would like an electronic copy of the summary of this survey, please provide your email here :

Please use the space below for any comments you wish to make.

Thank you very much for your time and effort. Your answers will be kept confidential.

Please return this questionnaire to us. Simply seal it in the enclosed business reply mail envelope and drop it in the mail.