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ESSAYS ON THE DESIGNS AND BENEFITS OF LAND CONSERVATION PROGRAMS

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by

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ESSAYS ON THE DESIGNS AND BENEFITS OF LAND CONSERVATION PROGRAMS

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This dissertation analyzes the policy designs and economic benefits of a land conservation practice called prairie strips. The first chapter investigates the impact of policy designs on individual household preferences. The study measures the value that Iowa residents place on the ecosystem services of prairie strips and determines if that value changes under different policy designs. The policy design treatment varies in who runs the program and who has enrollment priority. The willingness to pay (WTP) for ecosystem services is estimated using stated preferences from a choice experiment. Results indicate significant public support for expanding and funding the prairie strips program under all policy designs. WTP for the program is highest for the management by non-governmental organizations (NGOs) and enrollment priority to the landowners with good environmental stewardship in the past.

The second chapter analyzes the role of farming experiences, conservation experiences, and satisfaction of the existing status of the environment in explaining variation in preferences of prairie strips. The results suggest that those with farm experiences prefer new conservation alternatives significantly more than without farm experiences. Similarly, individuals who have past experience with conservation activities or education have substantially higher preference for water quality-related attributes. There is a significant inverse relationship between environmental satisfaction and preferences

for all the ecosystem services.

The last chapter examines the role of spatial variability of profit and crop insurance premium on site-specific land retirement decisions for a land retirement program such as the Conservation Reserve Program (CRP). It uses site-specific input and output data from a precision agriculture experimental plot in Illinois. The study introduces a decision framework to include site-specific yield and insurance premium cost in land retirement decisions. The findings indicate that using site-specific insurance premium costs benefits farmers by creating a different optimal land retirement plan with higher net profit. It also reduces the expense of insurance premiums. The new decision framework, thus, advises farmers on the best location and amount of farmland to enroll in CRP for a higher overall benefit.

I'd like to dedicate this work to my mother, Gauri Devi, to my wife, Nisha, and to my daughters Ana and Aarya

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Chapter 1

INTRODUCTION

The three chapters of this dissertation focus on measuring the impact of policy designs on the public valuation of ecosystem services from a farmland conservation program, finding the role of attitudes and experiences in valuation, and analyzing the welfare impacts of optimal siting of conservation practices. Specifically, the research examines the conservation practice of planting prairie strips (a conservation practice) in agricultural land. This study uses two sources of information. Data on ecosystem services valuation is from a stated preference choice experiment conducted with the public in Iowa. Spatially variable data from a precision agriculture experimental farm measures the optimal siting of conservation practices and the welfare impacts of alternative land retirement scenarios.

The first chapter investigates the impact of policy designs on individual household preferences. Conservation practices on agricultural land can provide significant environmental benefits such as reduced soil erosion and improved wildlife habitat. Incorporating prairie strips into working agricultural lands can provide such benefits and has recently been added as a supported practice in the USDA Conservation Reserve Program (CRP). Prairie strips are practices where perennial grass strips are incorporated within row-crop fields to improve soil, water, and biodiversity. Based on neoclassical economic theory, the ecosystem services of prairie strips is the basis for willingness to pay for the conservation practice of prairie strips. In practice, however, it may depend on how the program is designed and the socio-economic characteristics of the population. However, the relation of welfare gain from prairie strips ecosystem services to policy design and the socio-economics of the population is yet to explore. The current study measures the value that Iowa residents place on the ecosystem services (ES) provided by prairie strips and determines if that value changes under different policy designs. The policy design treatment varies in two aspects: who runs the program (state agency versus NGO) and who has enrollment priority (historically managed land versus degraded land). The willingness to pay (WTP) for ecosystem services is estimated using stated preferences from a choice experiment.

This study contributes to the newly established (in 2019) prairie strips Conservation Reserve Program (CRP) (CP-43) for guiding in successful goal setting, enrollment prioritizing, and implementing the conservation program. The values estimated for policy designs of prairie strips are public commitment towards those policies that help design sustainable conservation programs. Valuation at the policy design level contributes to an effective agricultural land management policy.

The second chapter measures the role of experiences and satisfaction in preferences for the conservation program. This study also uses the Iowa choice experiment data. Policy on farmland conservation is mainly designed based on public preferences for ecosystem services provided by the conservation. Targeted beneficiaries in policy designing are homogeneous representative populations having average values of preferences for those ecosystem services. Conservation policies designed for representative populations face challenges to maintain a long-term sustainable program that needs support from larger and heterogeneous populations. Given the difference in public experiences and satisfaction, policymakers' crucial question is how those differences affect preferences for farmland conservation and how much willingness to pay for those ecosystem services varies for that heterogeneous population. Household experiences with farming and conservation practices and satisfaction with the current state of the environment can influence preferences, valuation, and acceptability of farmland conservation practices. The present study analyzes the role and relative importance of farming experiences, conservation experiences, and status of satisfaction toward the current status of the environment in explaining variation in preferences and willingness to pay for ecosystem services of prairie strips farmland conservation in Iowa. The stated preference data of prairie strips and its' ecosystem services attributes are collected using a stated preference discrete choice experiment. A willingness to pay space specification of the Generalized Multinomial Logit (G-MNL) model accounts for preference and scale heterogeneity in current estimation.

The second chapter contributes to an emerging model of integrating individual behavior in policy design. Many studies exist on farmland conservation preferences of diverse socio-economics of the population. For example, researchers have explored the impact of income, age, gender, and education in preferences for ecosystem services of conservation practices. However, despite experiences and satisfaction are more in defining preferences than socio-economics, only a handful of researchers examined how experiences and satisfaction levels can shape preferences and willingness to pay. Understanding experiences is useful for policymakers to understand or explain the attitude and behavior of beneficiaries of a program. For example, it helps to understand farmers' preferences where farmers are both providers and consumers of the farmland ES and farmers should also share the cost of preserving farmland ES. This paper, thus, identifies beneficiaries to prioritize based on their background experiences and satisfaction level to get feedback on the program for the successful implementation of the prairie strips program in the future.

The last chapter examines the role of spatial variability of profit on site-specific land retirement decisions with an application to the Conservation Reserve Program (CRP). The US Farm Bill establishes voluntary conservation programs to encourage farmland retirement and adopt conservation practices on working lands. The landowner gets incentives to remove less productive and environmentally sensitive fields for agricultural purposes and reestablish them in natural vegetation that meets the conservation objectives. However, removing arable land from agriculture causes an opportunity cost in terms of revenue lost from crops that would otherwise have been produced. In the past, site-specific land retirement decision tools for farmland conservation assumed fixed crop insurance premiums within a plot. Farmers can save insurance costs and benefit more by strategically retiring the right plot sites if they use site-specific insurance premiums. The current study introduces a new decision framework for determining optimal site-specific farmland retirement for land retirement programs like the Conservation Reserve Program (CRP) with or without crop insurance cost consideration. Profit maximization simulation using site-specific data from an experimental precision agriculture plot in Effingham County, Illinois, in 2019 achieves this. The simulation makes use of site-specific corn inputs and outputs from the experimental units (sub-plots). The harvester's swath's sub-plots are combined to form a strip. As a result, the experimental plot includes several parallel strips that function as land retirement decision-making units. Crop Only (COS), Retirement Only (ROS), Crop and Fixed Insurance (CFIS), Crop and Retirement (CRS), Crop, Retirement, and Site-specific Insurance (CRSIS), and Crop, Retirement, and Fixed

Insurance (CRFI) are the six land retirement strategies compared in the current decision framework.

The third chapter contributes to providing a new decision framework that provides an economic guideline to the farmers for decision-making in CRP land retirement. The decision framework provides a foundation for using agronomic information and knowledge of farmers to guide economic decision-making at the farmland level. The use of a new decision framework provides more economic gain to the farmers than existing decision tools while having similar environmental benefits. Incorporating site-specific crop insurance cost components in farmland decision frameworks has introduced new precision agriculture information in land use planning. As crop insurance is an integral part of most of the farmland in the US, most farmers can benefit if they use the new decision framework for land retirement decision-making. This framework is also applicable in the cases where the farmers retire their land other than conservation purposes.

Chapter 2

THE IMPACT OF POLICY DESIGN ON WILLINGNESS TO PAY FOR ECOSYSTEM SERVICES

2.1 Introduction

Ecosystem services from farmland conservation are public good benefits (Costanza et al., 1997) and are primarily measured using methods that determine the willingness to pay (WTP) for those benefits (Loomis et al., 2000). Prairie strips, a farmland conservation practice, provide ecosystem services such as improved water quality, soil health, and biodiversity (Schulte et al., 2017). However, policymakers do not know how the public values the ecosystem services of prairie strips. Based on neoclassical economic theory, the WTP for prairie strips should be solely based on ecosystem services provided and income level of the people (Liebe et al., 2011). In practice, it may also depend on how the program is designed and the other socio-economic characteristics of the people. While the welfare gain from the ecosystem services and its relation to the socio-economics of the population are increasingly known (Schaefer et al., 2015), relation to policy design is a recent addition to ecosystem services assessment (Bergstrom and Ready, 2009). Particularly, the relation of welfare gain from prairie strips ecosystem services to policy design and the socio-economics of the population is not studied yet.

This paper analyzes the value to the public of implementing prairie strips conservation on private land in Iowa. It measures public preferences for ecosystem services of prairie strips under the interaction of two policy treatments. The first policy treatment compares the management of the program by a state agency with a non-government organization (NGO) like the Nature Conservancy. The second policy treatment compares an enrollment preference for landowners with degraded land to the landowners who have historically used conservation practices. The paper also explores how the differences in socio-economic characteristics like age, gender, education, and household income level affect preferences for the prairie strips' policy design and ecosystem services.

There are a number of reasons why this article is an important contribution. First, this is the first paper on the economic valuation of prairie ecosystem services that measures economic preferences of public for planting prairie grasses into private land for farmland conservation. Past studies on such valuation assigned monetary value to biophysical units of naturally grown prairie grasses in prairie pothole area (Gascoigne, 2011; Gleason et al., 2011). Specifically in Iowa, respondents' perspectives on multi-benefit agriculture like integrating prairie strips are explored (Arbuckle et al., 2015) but the public economic preferences for the ecosystem services are not.

Second, it creates new insights for policy design and land use decision making in case of prairie strips. The values estimated for policy designs of prairie strips are public commitment towards those policies. Valuation at policy design level contributes to effective agricultural land management policy (Johnston and Duke, 2007; Duke et al., 2012). Non-market valuation of ecosystem services that considers policy design has a greater effect on the policy process due to an alignment with policy objectives (Banzhaf, 2010). The current study helps in guiding successful goal setting, enrollment prioritizing, and implementing the newly established (in 2019) prairie strips as a Conservation Reserve Progam (CRP) supported practice (CP-43). The differences in value to the public for different ecosystem services of prairie strips help CRP prioritize their program information dissemination. The differences in acceptance rate for the public for different payment options for prairie strips policy designs are essential for designing sustainable programs and funding.

The analysis uses data from a survey of Iowa residents designed for a stated preference choice experiment. The survey used a web-based platform to collect responses in November and December 2019 and used a fractional factorial design with four ecosystem services attributes and a one-time payment attribute. The ecosystem services attributes are a decrease in nutrient loss to water, decrease in sediment loss, increase in the number of pollinators, and increase types of birds. The payment attribute is a one-time cost as annual tax from the household. Estimation uses the Generalized Multinomial Logit Model (G-MNL) that accounts for heterogeneity in both taste and scale of preferences (Fiebig et al., 2010) and follows a random utility model (McFadden, 1974).

Results show a significant positive willingness to pay (WTP) for ecosystem services provided by prairie strip. Decrease nutrient loss to water has higher WTP than other ecosystem services of prairie strips. Similarly, the estimated value of ecosystem services varied between the policy designs. The public preferences are significantly high for a program run by NGO and enrollment priority to the landowner with historically managed land (NGOHist policy) compared to other policy designs. The acceptance rate for the payment for ecosystem services of prairie strips is also high with NGOHist policy. The difference in socio-economic characteristics of the households resulted in significant taste and scale heterogeneity. High income and higher educated respondents always valued more to ecosystem services of prairie strips. Our study's information on public preferences helps to plan enrollment and funding of the newly established prairie strips conservation reserve program.

2.2 Background

The state of Iowa is a major corn producer and contributes significant amounts of nitrogen and phosphorous to the Gulf of Mexico (Alexander et al., 2008). Iowa is one of the highest polluter states in terms of the number of surface waters contaminated by excessive nutrients, toxins, chemicals, and soil sediment concentrations (Liebman et al., 2013). The development of conventional agricultural systems has also resulted in a significant loss of biodiversity, including a dominant land cover of Tall-grass prairie. Currently, Iowa's prairie communities cover less than 0.1 percent of the area that existed before the Euro-American settlement (Liebman et al., 2013).

The United States Department of Agriculture (USDA) Conservation Reserve Program started in 1985 and has enrolled many landowners from Iowa since its inception. One of the significant challenges of CRP is the voluntary enrollment policy. The CRP acreage decreased in the recent past, from 2.20 million acres in 1994 to 1.75 million acres in 2019 in Iowa. Increased corn use for bio-ethanol production and high corn price significantly contributed to such a decrease (Secchi et al., 2009).

Prairie strips are strips of perennial grasses within row crop fields and are tools to improve soil, water, and biodiversity (Schulte et al., 2017). A prairie strip can be along the crop field outline (contour buffer strip) or field edge (filter strip). It includes perennial native grasses and wildflowers that mitigate runoff during heavy rainfall. The incorporation of small amounts of prairie into strategic positions within corn and soybean fields may enhance soil, water, pollinators, and wildlife protection (Schulte et al., 2017). The Science-based Row Crop Trails Integrated with Prairie Strips (STRIPS) team in Iowa has been operating as a pilot program for more than ten years, during which it has helped match funding to landowners to incorporate prairie strips and analyzed the impacts on environmental indicators. The USDA named prairie strips (CP-43) as a supported practice under the CRP, starting in December 2019. The expansion to CRP has added exposure and established funds for prairie strips.

CP-43 is the continuous sign-up federal USDA-CRP program under the Clean Lakes, Estuaries and Rivers (CLEAR) initiative of the USDA. The program focuses on soil erosion prevention, water quality improvements, and wildlife protection. Unlike the general CRP, the land will be automatically accepted for CRP if it meets the requirements and the acres are available. Aside from an annual payment, the cost-share and incentives cover most of the expense of the establishment. Financial incentives include annual rental payments, up to 50 percent cost-sharing payments for establishments, 5 percent practice incentive payments, and sign-up incentives equal to 32.5 percent of first-year rental payments.

2.3 Data and Methods

2.3.1 Survey and policy treatments

The data for this study is collected using a survey designed specifically for stated preference for prairie strips' ecosystem services. Respondents obtained information on ecosystem services improvement as a prairie strips conservation program between a landowner and an agency. The survey informed respondents about the ecosystem services of prairie strips. Survey then proposed an expansion of the prairie strips program. Respondents are informed that the expansion is only possible if the current study supports it. Respondents were told that if the program was expanded, a one-time payment would be added to the 2020 state income tax to fund the program. The new tax dollars collected would be placed into a special fund set up for the project's construction and maintenance over 30 years.

The survey randomized the two policy treatments. The first treatment has two management options of the program. First, the state will manage the fund, and the program implemented through a state agency such as the Iowa Department of Agriculture and Land Stewardship (IDALS). Second, the state will manage the fund, and the state will contract with an external organization (an NGO) such as The Nature Conservancy to implement the program. The second treatment distinguishes enrollment priority to the program. First, the program will prioritize enrollment of highly degraded land and, the second program will prioritize landowners who have historically maintained strong conservation practices. The interaction of two treatment provides four mutually exclusive sample of respondents for the policy designs given as in table 2.1. Policy designs are state-run and enrollment priority to degraded land (StateDeg) policy, state-run and enrollment priority to historically managed land (StateHist) policy, NGO run and enrollment priority to degraded land (NGODeg) policy, and NGO run and enrollment priority to the landowner with historically managed land (NGO-Hist) policy. State or federal agency funds and regulates the program, whatever be the policy design.

Table 2.1: Policy treatments used in the survey of stated preference choice

Treatments	Program run by	Enrollment Priority to
StateDeg	State agency (IDALS)	landowner with highly degraded land
StateHist	State agency (IDALS)	landowner with historically maintained strong conservation practices
NGODeg	NGO (The Nature Conservancy)	landowner with highly degraded land
NGOHist	NGO (The Nature Conservancy)	landowner with historically maintained strong conservation practices

IDALS = Iowa Department of Agriculture and Land Stewardship

2.3.2 Sample

An on-line panel from Dynata company (https://www.dynata.com/) recruited the respondents. Members of these survey panels previously expressed willingness to participate in such social research studies and provide their socio-demographic information. The panel included all Iowa resident aged 19 or older and surveyed in November and December of 2019. The Institutional Review Board (IRB) and Research Compliance Services through the University of Nebraska-Lincoln (UNL) Human Research Protection Program (HRPP) approved the survey questionnaire. The survey company ensured that all responses are confidential, and respondents signed the consent before participation in the on-line survey. The sample includes 1200 Iowa households. Following the convenience sampling method, the survey asked 2096 individuals to get the 1200 sample responses. The response rate is thus 57.25 %. Figure 2.1 presents the respondents' socioeconomic and demographic characteristics. Figure 2.1 shows that the sample is representative of the Iowa public in most characteristics, including age and income. The sample has 7% more females than the population of Iowa and has a higher response rate among college-educated respondents. Table 2.2 presents the discrete categories used in our current analysis. The only significant difference between the sample and the Iowa population is the proportion with a college degree. Our sample has 40.1 percent of respondents with college degree compared to 26.86 percent of the Iowa population.

Table 2.2: Summary of respondents (n=1200) socioeconomic characteristics

Characteristics	Code	Sample percent	Population percent
Age 55 or above	Older	38.8	39.9
Female	Female	57.4	50.7
At least 4 years College	College	40.1	26.9
Annual household income more than $ 75,000	High-income	36.3	40.4

*Source: US Census Bureau, American Community Survey, 2019.

The survey also did very well in the representation of the sample from geographical units of Iowa. Figure 2.2 shows how the sample represents the population of Iowa by county. Out of 99 counties of Iowa, the survey data includes respondents from 97 counties. Our sample does not have respondents from Ringgold and Monona county that collectively account for less than 0.005 % of the population. The sample's representation is proportionate to the population of counties. For example, the highest populated Polk county with dark yellow color in the map (> 400K population) has the highest number of the sample (> 150).

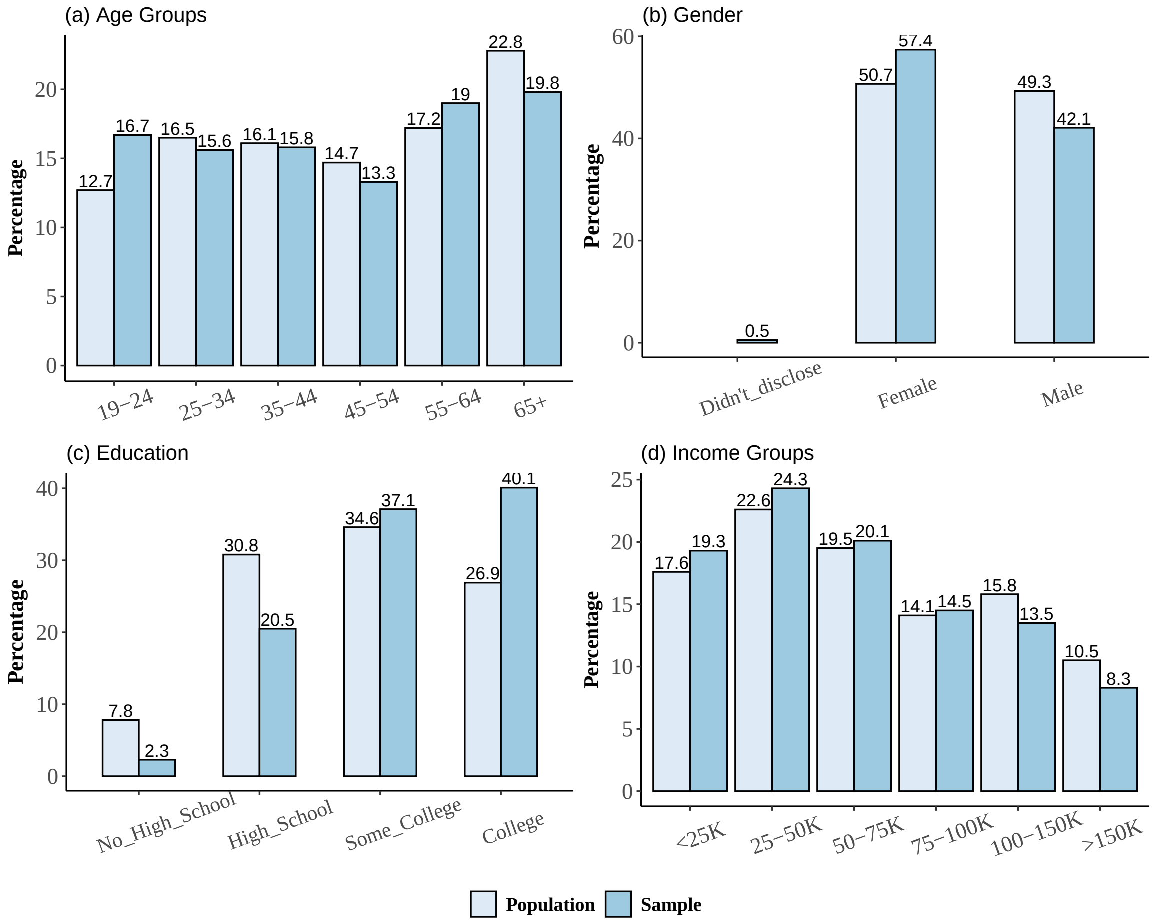

Figure 2.1: The distribution of sample and population by socio-economic characteristics

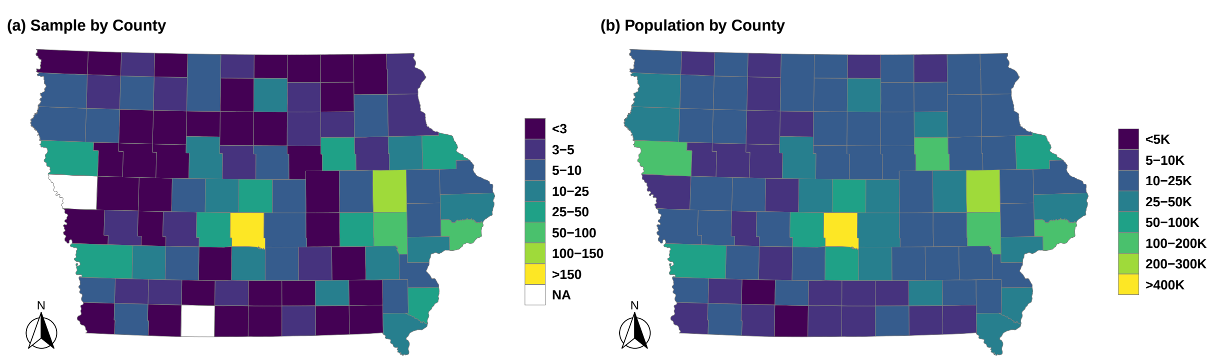

Figure 2.2: The geographic distribution of sample and population by counties of Iowa

2.3.3 Choice model

The current study used a choice-based stated preference design using the fractional factorial method. Each choice set has five attributes (Table 2.3). Four attributes are ecosystem services attributes, i.e., decrease nutrient loss to water, decrease sediment loss, increase pollinators, and increase types of birds. The fifth attribute is a one-time cost for the household to expand the prairie strips program. Each ecosystem services attribute has three levels and the one-time payment attribute has four levels. Level of the attributes are based on a finding from a study in Iowa (Schulte et al., 2017) and consultation with researchers from the Science-Based Trials of Rowcrops Integrated with Prairie Strips (STRIPS) team. Out of 324 (i.e., 4×3^4) possible choice options, the fractional factorial design identified 36 non-trivial choice options. Each choice set has three options: two with new prairie management policies (out of 36 choice options) and one status quo (always same). The survey used a blocked design to avoid respondent fatigue, with three blocks of six questions per block. Each individual answered one block of choice questions. Figure 2.3 presents a sample question used in the survey.

2.3.4 Empirical model

The empirical analysis uses the generalized multinomial logit model (G-MNL) to account for heterogeneity in the value of ecosystem service attributes and the individual-specific error. The Generalized Multinomial Logit model (G-MNL) is based on random utility model (McFadden, 1974) and outperforms other similar logit models as it incorporates both scale and preference heterogeneity (Fiebig et al., 2010). The scale variations of error explains the heterogeneity of individuals' preferences significantly

Table 2.3: Summary of attributes, definition, and levels used for each attribute in the choice question

Attributes	Definition	Unit	†Levels
Decrease nutrient loss to water	Reduction in total phosphorus, total nitrogen, or nitrate-nitrogen concentrations	% less	50, 70, 90
Decrease sediment loss	Reduction in sediment loss (loss of topsoil with nutrients)	% less	55, 75, 95
Increase number of pollinators	Increase in pollinator abundance	times increase	2, 4, 6
Increase types of birds	Increase in bird species richness	% increase	50, 100,150
One time cost to you	Willingness to pay for ecosystem services by prairie strips [as one time tax]	$	25, 50, 100, 200

† Levels are based on the study by Schulte-Moore et al., 2017 and expert consultation

Q. Which policy choice option you would prefer among the following?

	Option A	Option B	Option C
Decrease Nutrient Loss to Water	90 % Less	50% Less	No change
Decrease Sediment Loss	95% Less	75% Less	No change
Increase Number of Pollinators	2 Times More	6 Times More	No change
Increase Types of Birds	100% More	150% More	No change
One-time Cost to You	$25	$200	$0
Your most Preferred Option	☐	☐	☐

Figure 2.3: Sample question of the choice experiment

in choice models (Louviere et al., 1999, 2000). Four ecosystem services attributes and one alternative specific constant attribute in our study are random and have a multivariate normal distribution. The indirect utility function $\boldsymbol{U}$ of an respondent n from alternative j and t choice scenarios for respondents under G-MNL model is given by (Fiebig et al., 2010)

$$U_{njt} = \underbrace{[\sigma_n\beta + \gamma\eta_n + (1-\gamma)\sigma_n\eta_n]}_{\mathrm{B}_n} \boldsymbol{X}_{njt} + \varepsilon_{njt} \tag{2.1}$$

The G-MNL model is specific in how the coefficient of attributes (B_n) are defined. β represents fixed coefficients for vector of attributes $\boldsymbol{X}_{njt}$ and ε_{njt} is idiosyncratic error term. B_n has components of taste heterogeneity given by η_n which is the vector of respondent-specific standard deviation from β and scale heterogeneity given by σ_n which is the scale of error term for respondent n.

The γ [-∞ to $+\infty$] is scalar weighting parameter defines whether scaling would be only for fixed coefficient β or also for individual specific variation η_n (Keane and Wasi, 2013). If γ is 1 the $\mathrm{B}_n = \sigma_n\beta + \eta_n$, called G-MNL-I. If the γ is '0' $\mathrm{B}_n = \sigma_n(\beta + \eta_n)$, called G-MNL-II. The standard deviation in G-MNL-I is independent of the scale factor σ_n, while both mean and standard deviation in G-MNL-II differ in proportion to the σ_n.

We estimated the model in willingness to pay space directly (Train and Weeks, 2005; Sonnier et al., 2007; Scarpa et al., 2008). First, we separate all attributes $\boldsymbol{X}_{njt}$ into one time payment attribute p_{njt} and vector of random attributes $\boldsymbol{x}_{njt}$ to obtain equation 3.3.

$$U_{njt} = \underbrace{[\sigma_n \beta + \gamma \eta_n + (1-\gamma)\sigma_n \eta_n]}_{\beta_n} \boldsymbol{x}_{njt} - \underbrace{[\sigma_n \alpha + \gamma \eta_n + (1-\gamma)\sigma_n \eta_{\alpha n}]}_{\alpha_n} p_{njt} + \varepsilon_{njt} \tag{2.2}$$

Where α is mean price coefficient for sample and α_n is individual specific price coefficient. We normalized the α_n to '1' to yield the WTP space specification in the equation 3.5, where coefficients β^* itself is the willingness to pay.

$$U_{njt} = \underbrace{[\sigma_n \beta^* + \gamma \eta_n^* + (1-\gamma)\sigma_n \eta_n^*]}_{\beta_n^*} \boldsymbol{x}_{njt} - p_{njt} + \varepsilon_{njt} \tag{2.3}$$

Having possible choice sequence of $y_{nt} = \{y_{n1}, y_{n2}, \ldots, y_{nT}\}$ for individual n at choice scenario t, the probability that individual n chooses alternative j is obtained by:

$$P(y_{nt} = j|\boldsymbol{x}_{nt}) = \frac{1}{R} \sum_{r=1}^{R} \frac{\exp\left([\sigma_n \beta^* + \gamma \eta_n^* + (1-\gamma)\sigma_n \eta_n^*]\boldsymbol{x}_{njt} - p_{njt}\right)}{\sum_{k=1}^{J} \exp\left([\sigma_n \beta^* + \gamma \eta_n^* + (1-\gamma)\sigma_n \eta_n^*]\boldsymbol{x}_{nkt} - p_{nkt}\right)} \tag{2.4}$$

The probability is simulated from the multivariate normal distribution of random attributes over R draws. Our estimation used 1000 Halton draws (Train, 2009). The coefficients vector (β^*) of random attributes are correlated. The simulated maximum likelihood (MSL) method estimates the likelihood function of the G-MNL specification .

The scaling parameter (σ_n) is defined as a function of respondents socio-economic characteristics and policy designs. Scaling includes ecosystem services attributes as well as alternative specific constant, so the model is a full-scale model (Hess and Train, 2017). The person-specific scale (σ_n) at choice scenario *'t'* is the function of respondents' characteristics and policy options in our estimation that can be written as:

$$\sigma_n = \exp(\bar{\sigma_n} + \mu \boldsymbol{Z}_{nt} + \tau v_{0n}) \tag{2.5a}$$

$$\begin{aligned}\sigma_n = \exp(&\bar{\sigma_n} + \mu_1 StateDeg_{nt} + \mu_2 StateHist_{nt} + \mu_3 NGODeg_{nt} + \mu_5 Older_{nt} \\ &+ \mu_4 Female_{nt} + \mu_6 College_{nt} + \mu_7 Highincome_{nt} + \tau v_{0n})\end{aligned} \tag{2.5b}$$

Where, $\boldsymbol{Z}_{nt}$ consists of a attributes vector for person n in scenario t. The $\boldsymbol{Z}_{nt}$ contains indicator variables for the four policy treatments StateDeg, StateHist, NGODeg, and NGOHist (= '0' for identification), and indicator variables for four individual characteristics female (vs. male = 0), older (vs. younger = 0), college (vs. no college =0), and high income (vs. low income =0). μ is a vector of parameters of Z_{nt}, representing the marginal effect of $\boldsymbol{Z}_{nt}$ on the scale factor. For the identification of β^* in the model, the expected value of σ_n is normalized to have "1" with standard deviation of τ that gives $\bar{\sigma_n} = -\tau^2/2$ and $E(\sigma_n) = 1$ with scalar v_{0n} distributes to a normal $\mathcal{N}(0, 1)$ (Fiebig et al., 2010).

The estimates from the G-MNL model in equation 3.5 are the unconditional coefficients vector for ecosystem services attributes (β^*) represented as $g(\beta^*_n|\theta)$. The parameter θ represents mean and standard deviation from a multivariate normal distribution of β^*. Bayes' rule is used to derive posterior distribution of the coefficients that provides an individual-specific conditional estimator $f(\beta_n^*|y_n, \boldsymbol{x}_n, \theta)$(Train, 2009). If $P(y_{nt}|\boldsymbol{x}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta})$ represents the probability of observed sequence of choices y_{nt} conditioned on attributes $\boldsymbol{x}_{nt}$, and unconditional values of coefficients $\widehat{\beta_{nr}^*}$ and their parameters $\widehat{\theta}$, the simulated conditional estimator, conditioned on individual-specific data is (Train, 2009; Greene, 2012).

$$\widetilde{\beta_n^*} = \ Est.\ E[\beta_n^*|y_n, \boldsymbol{x}_n, \theta] = \mathrm{E}\left[\frac{1/R\sum_{r=1}^{R}\widehat{\beta_{nr}^*}\Pi_t P(y_{nt}|\boldsymbol{x}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta})}{1/R\sum_{r=1}^{R}\Pi_t P(y_{nt}|\boldsymbol{x}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta})}\right] = \sum_{r=1}^{R}\widehat{\beta_{nr}^*}\times\widehat{W_{nr}} \tag{2.6}$$

Where, $\widehat{\beta_{nr}^*} = \beta^* + \eta_{nr}$ is individual n specific unconditional coefficients vector with 'r' random draw. $\widehat{W_{nr}} = P(y_{nt}|\boldsymbol{x}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta}) \ / \ \sum_{r=1}^{R} P(y_{nt}|\boldsymbol{x}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta})$ represents the weight that adjust the individual condition so that $0 < \widehat{W_{nr}} < 1$ and $\sum_{r=1}^{R}\widehat{W_{nr}} = 1$. The distribution of individual-specific coefficients of attribute $\widetilde{\beta_n^*}$ is conditional on the observed sequence of choices $y_{nt} = \{y_{n1}, y_{n2}, \ldots, y_{nT}\}$ for individual n. The data analysis uses the R (4.0.3) "mlogit" and "gmnl" packages (Team, 2021).

2.4 Results

2.4.1 Model estimates

Table 2.4 presents results of the model specification from equation (3.5) used for current study. The model estimation is in willingness to pay space directly. For consistency across attributes and to increase the convergence of simulation model, all attribute changes are converted into a percent change (i.e.,100%, 300%, and 500% increase for pollinator improvement). Thus, the parameter estimates give the estimated willingness to pay for a 1% increase in attribute levels for all attributes other than the alternative specific constant (ASC). The alternative specific constant provides the willingness to pay for choosing new prairie strips management compared to the status quo that is additional willingness to pay not captured by the attributes included in the model. As two policy alternatives are different from the status-quo alternative but have no meaningful difference themselves, alternative one and alternative two have common alternative specific constant (ASC) in the analysis.

Table 2.4: Estimates of Generalized Multinomial Logit Model (G-MNL)

	Mean		Standard Deviation	
	Estimate	St Error	Estimate	St Error
Random attributes:				
Decrease Nutrient Loss to Water	0.69***	−0.09	0.47***	0.06
Decrease Sediment Loss	0.06	−0.03	0.12***	0.02
Increase Number of Pollinators	0.06***	−0.01	0.04***	0.01
Increase Types of Birds	0.02	−0.03	0.16***	0.02
Alternative Specific Constant	69.08***	−10.28	65.82***	6.44
Scale attributes:				
Intercept for scale	−4.18***	−0.14		
Scale of StateDeg Policy	0.57***	−0.11		
Scale of StateHist Policy	0.49***	−0.09		
Scale of NGODeg Policy	0.66***	−0.09		
Scale of Older	0.42***	−0.08		
Scale of Female	0.31***	−0.07		
Scale of College	0.56***	−0.08		
Scale of High income	−0.25***	−0.07		
Variance parameter in scale (τ):	2.38***	−0.18		
Weighting parameter (γ):	−0.06***	−0.01		
Model fit:				
Number of observations	7200			
Log-likelihood at zero (MNL)	−7910.01			
Log-likelihood at convergence (MNL)	−7060.43			
Log-likelihood at convergence (G-MNL)	−5346.50			
McFadden Pseudo-R^2	0.32			
Likelihood ratio $\chi^2(24)$ (MNL vs. G-MNL)	3427.90***			
Info. criterion: AIC for MNL model	14132.86			
Info. criterion: BIC for MNL model	14174.15			
Info. criterion: AIC for G-MNL model	10753.00			
Info. criterion: BIC for G-MNL model	10959.46			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

StateDeg = Program run by State agency and enrollment priority to landowner with degraded land; StateHist = Program run by state agency and enrollment priority to landowner with historically managed land; NGODeg = Program run by NGO and enrollment priority to landowner with degraded land; NGOHist = Program run by NGO and enrollment priority to landowner with historically managed land

We first estimated the Multinomial Logit (MNL) model, which assumes all the attributes are fixed (results not reported). The analysis compared MNL with results from the generalized Multinomial Logit (G-MNL) model. The standard Multinomial Logit model assumes the independence of irrelevant alternative (IIA). Hausman Mc-

Fadden test finds no IIA in our data (Appendix I).

The model fit parameters tested justifies the use of G-MNL model. The McFadden pseudo-R-squared value explains that attributes used in our study fits the model by 32.4 % better than when only intercepts are used in the Multinomial Logit (MNL) model. The log-likelihood value improved by 24.26% in the G-MNL model (-5346.50) compared to that of the MNL model(−7060.42). The likelihood ratio test (LR test) showed that the G-MNL model's likelihood is significantly better than the Multinomial Logit model. The values from Aikie Information Criterion (AIC) and Bayesian Information Criterion (BIC) are lower for the G-MNL model than MNL.

Indicator variables of policy designs and socio-economic characteristics are scale variables in our analysis. The policy designs consist of the program run by a state agency and enrollment priority to the landowner with degraded land (StateDeg Policy), program run by a state agency, and enrollment priority to the landowner with historically managed land (StateHist Policy). Policy design with NGO operate the program are a program run by NGO and enrollment priority to the landowner with degraded land (NGODeg Policy), and program run by NGO and enrollment priority to the landowner with historically managed land (NGOHist Policy). Socio-economic characteristics in model include dummies for age, gender, education, and income of the respondents. The reference sample for the estimation is NGOHist policy with younger, male, no college, and low-income group. The scale of constant ($\bar{\sigma_n}$) represents the reference sample.

The mean coefficients' estimates for the reference sample are \$0.69 for decreased nutrient loss to water, \$0.06 for decreased sediment loss, \$0.06 for increase number of pollinators, and \$0.02 for increase types of birds. As coefficients represent WTP, the mean willingness to pay for a 1% more decrease in nutrient loss to water is \$0.69, for example. The willingness to pay for choosing the alternative new policy with prairie strips is \$69.08 for the reference sample. The positive alternative specific constant (ASC) coefficients indicate overall support for new conservation funding, even if that funding is not directly tied to the four attributes included in the study.

The standard deviation of all ecosystem services attributes, including alternative specific constant is statistically significant supporting heterogeneous taste preferences for the attributes. The estimate also shows the scale of preference for ecosystem services are heterogeneous even after having correlated random attributes (Appendix-II). The τ parameter captures the scale heterogeneity in the G-MNL model. It is the standard deviation of the individual respondent specific scale of idiosyncratic error. With a value of 2.38 and a standard error of -0.18, the scale parameter, τ is statistically significant and shows scale heterogeneity in the results.

The scale of StateDeg policy (0.57), StateHist policy (0.49), and NGODeg policy (0.66) are all significantly different and positive compared to the reference sample with NGOHist policy. The scale estimates for policy support that there is significantly low marginal effect of the respondents with NGOHist policy on scaling factor (σ_n) compared to other policy designs.

The positive and significant values for the scale of older (0.42), female (0.31), and college (0.56) indicates that their marginal effects on scale factor are higher compared to respondents having younger, male, and no college degree respectively. This results respondents with older, female, and college has more variation in their choices compared to their respective counters. The high-income respondents have a negative and significant value (-0.25) of scale parameter, which supported less marginal effects on scale factor and less variation in their choices than respondents with a low income. With a value of -0.06, the estimation of the weighting parameter γ is statistically significant that represents the G-MNL-II model, where the variance of residual taste heterogeneity increases with scale.

2.4.2 Willingness to pay estimates

Table 2.5 provides the marginal willingness to pay estimates for different policy designs and ecosystem services attributes. The estimates are conditional WTP estimate from unconditional distribution of WTP using Bayes rule (Train, 2009) estimated using equation (3.7) after estimating model from equation (3.5) and scale of policy designs using equation (2.5b). The number with letter subscript represents the mean estimate of willingness to pay for the specific attribute and policy design. The numbers separated by a comma within large braces are 95% confidence intervals of the mean estimates.

The NGOHist policy design has a higher WTP than other policy design for attributes decrease nutrient loss to water, increase number of pollinators, and ASC. The subscript letter in mean estimates the significant differences between the mean of policy designs. For 1 % more decrease in nutrient loss to water, policy design of StateDeg, StateHist, NGODeg, NGOHist has \$1.07, \$1.08, \$1.04, and \$1.21 willingness to pay respectively, that for increase number of pollinator are \$0.10, \$0.10, \$0.10, and \$0.11 respectively. The WTP for ASC of policy StateDeg is \$125.44, StateHist is \$125.82, NGODeg is \$122.65, and NGOHist is \$141.12. Marginal WTP estimates for decreased sediment loss and increased types of birds for the policies are not significantly different.

Table 2.5: Marginal willingness to pay estimate for attributes under different policy designs

	StateDeg Policy (mean + 95 %CI)	StateHist Policy (mean + 95%CI)	NGODeg Policy (mean + 95 %CI)	NGOHist Policy (mean + 95 % CI)
Decrease nutrient loss to water	1.07_b	1.08_b	1.04_b	1.21_a
	[0.99, 1.16]	[0.99, 1.16]	[0.96, 1.13]	[1.11, 1.30]
Decrease sediment loss	0.13_a	0.13_a	0.12_a	0.14_a
	[0.11, 0.14]	[0.11, 0.14]	[0.11, 0.14]	[0.13, 0.16]
Increase number of pollinators	0.10_b	0.10_b	0.10_b	0.11_a
	[0.09, 0.11]	[0.09, 0.11]	[0.09, 0.11]	[0.10, 0.12]
Increase types of birds	0.08_a	0.07_a	0.08_a	0.08_a
	[0.06, 0.09]	[0.06, 0.09]	[0.06, 0.09]	[0.07, 0.10]
Alternative specific constant	125.44_b	125.82_b	122.65_b	141.12_a
	[115.96, 134.92]	[116.35, 135.29]	[113.47, 131.83]	[130.77, 151.46]

StateDeg = Program run by State agency and enrollment priority to landowner with degraded land; StateHist = Program run by state agency and enrollment priority to landowner with historically managed land; NGODeg = Program run by NGO and enrollment priority to landowner with degraded land; NGOHist = Program run by NGO and enrollment priority to landowner with historically managed land; Significant differences between means of policy designs are shown by subscript letters

The table 2.6 shows the estimated WTP when 10% of the potential cropland is planted with prairie strips. All of the information provided to respondents and the attribute levels are based on prior research that estimates the benefit of incorporating prairie strips on 10% of a field. The mean estimated decrease in nutrient loss to water, decreases sediment loss, increases pollinators, and increases types of birds with 10% prairie are 75% less, 90% less, 300% more, and 100% more respectively compared to no prairie strips or status quo (Schulte et al., 2017). The NGOHist policy has significantly higher WTP than StateDeg, StateHist, and NGODeg policy, with overall WTP of NGOHist ($286.11) compared to StateDeg ($254.31), StateHist ($255.10), and NGODeg ($248.62) policies. The household preferences for decreased nutrient loss to water are highest, followed by increased pollinators, decreased sediment loss, and increased types of birds, respectively, for all policy designs.

Table 2.6: Willingness to pay under different policy designs for the prairie strips planted in 10% of the environmentally sensitive farmland

	StateDeg Policy (mean + 95 %CI)	StateHist Policy (mean + 95%CI)	NGODeg Policy (mean + 95 %CI)	NGOHist Policy (mean + 95 % CI)
Decrease nutrient loss to water	80.41_b	80.87_b	78.35_b	90.52_a
	[74.07, 86.74]	[74.46, 87.28]	[72.19, 84.49]	[83.57, 97.48]
Decrease sediment loss	11.33_a	11.22_a	11.18_a	12.66_a
	[10.06, 12.59]	[9.95, 12.48]	[9.95, 12.41]	[11.28, 14.05]
Increase number of pollinators	29.57_b	29.82_b	28.83_b	33.36_a
	[27.35, 31.79]	[27.57, 32.05]	[26.67, 30.99]	[30.93, 35.80]
Increase types of birds	7.56_a	7.39_a	7.62_a	8.44_a
	[5.76, 9.37]	[5.58, 9.19]	[5.96, 9.27]	[6.48, 10.39]
Alternative specific constant	125.44_b	125.82_b	122.65_b	141.12_a
	[115.96, 134.92]	[116.35, 135.29]	[113.47, 131.83]	[130.77, 151.46]
Overall WTP for 10% of prairie strips	254.31_b	255.10_b	248.62_b	286.11_a
	[88.99, 102.80]	[236.84, 273.37]	[230.62, 266.63]	[266.09, 306.13]

Note: StateDeg = Program run by State agency and enrollment priority to landowner with degraded land; StateHist = Program run by state agency and enrollment priority to landowner with historically managed land; NGODeg = Program run by NGO and enrollment priority to landowner with degraded land; NGOHist = Program run by NGO and enrollment priority to landowner with historically managed land; Significant differences between means of policy designs are shown by subscript letters

Figure 2.4 provides a density plot of marginal willingness to pay estimate for ecosystem services attributes (a to d), alternative specific constant(e), and overall willingness to pay estimate(f) for 10% of prairie strips. The density plots of ecosystem services attribute (a to d) shows that NGOHist policy has a more flat and right-shifted density distribution than other policy designs for all four attributes.

2.4.3 Socio-economic characteristics and willingness to pay estimates

The scale of socio-economic characteristics of respondents in our analysis are significant in explaining the differences in WTP (table 2.7). The superscript and subscript

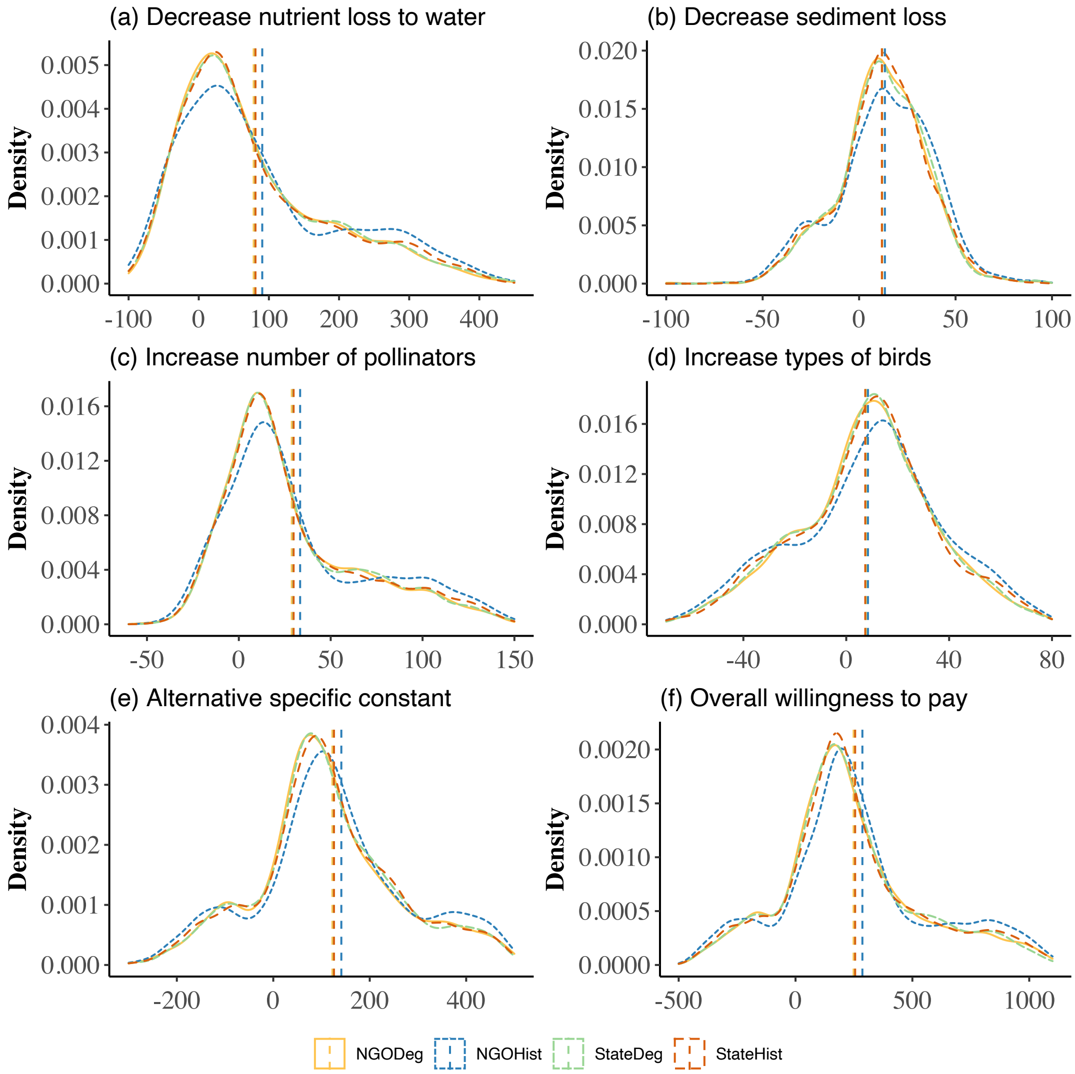

Figure 2.4: Density plot of willingness to pay for random attributes (a-e), and overall willingness to pay estimate for 10% of prairie strips (f)-the vertical dashed lines represent the mean estimates

letters in numbers of the table give the differences between socio-economic characteristics and policy designs, respectively. The horizontal line between the rows in table separates the socioeconomic attributes, and thus, superscripts are comparable within this boundary. For example, WTP is not significantly different across the two age groups for all policy designs. However, analyzed within same agegroup, respondents with NGOHist policy has significantly higher WTP than any other policy for both age groups.

Respondents with college degree have significantly higher WTP than with no college degree for all policy designs. When analyzed only within a education level, respondents with no college degree have significantly higher WTP of $280.94 for NGOHist policy compared to all other policies. However, the WTP is not significantly different for all policies for only respondents with college degree. This finding suggest that though policy attributes have a significant role in defining willingness to pay, respondents having higher education always has a higher willingness to pay regardless of policy design.

Willingness to pay is not significantly different between male and female respondents for all policies. However, analyzed only within a gender, a female with NGOHist policy has significantly higher WTP of $286.39 than StateHist and NGODeg policy and not significantly different with StateDeg policy. A male with NGOHist policy has significantly higher WTP of $285.72 compared to all other policies.

Analyzed for income levels of households, high-income households have a significantly higher willingness to pay compared to low income for all policy designs. The WTP estimate for different policy designs is, however, not significantly different when compared only within high-income respondents, and is significantly higher WTP of $263.84 for NGOHist policy is significantly higher than other policies.

Table 2.7: Overall willingness to pay for different individual characteristics of respondents for the prairie strips planted in 10% of environmentally sensitive farmland

	StateDeg Policy (mean + 95 %CI)	StateHist Policy (mean + 95%CI)	NGODeg Policy (mean + 95 %CI)	NGOHist Policy (mean + 95 % CI)
Older	$^{a}250.28_{b}$	$^{a}256.56_{b}$	$^{a}245.23_{b}$	$^{a}283.15_{a}$
	[222.84, 277.72]	[228.59, 284.52]	[217.67, 272.78]	[252.72, 313.59]
Younger	$^{a}256.63_{b}$	$^{a}254.27_{b}$	$^{a}250.58_{b}$	$^{a}287.81_{a}$
	[232.63, 280.63]	[230.37, 278.17]	[227.02, 274.13]	[261.53, 314.08]
College	$^{a}261.49_{a}$	$^{a}260.59_{a}$	$^{a}257.87_{a}$	$^{a}293.86_{a}$
	[236.02,286.97]	[234.46, 286.97]	[232.35, 283.384]	[265.56, 322.16]
No college	$^{b}249.524_{b}$	$^{b}251.443_{b}$	$^{b}242.460_{b}$	$^{b}280.939_{a}$
	[224.32, 274.73]	[226.44, 276.45]	[217.70, 267.22]	[253.37, 308.51]
Female	$^{a}255.45_{ab}$	$^{a}254.43_{b}$	$^{a}248.12_{b}$	$^{a}286.39_{a}$
	[231.51, 279.39]	[230.55, 278.31]	[224.62, 271.62]	[312.64, 260.15]
Male	$^{a}252.78_{b}$	$^{a}256.01_{b}$	$^{a}249.30_{b}$	$^{a}285.72_{a}$
	[224.62, 280.93]	[227.59, 284.43]	[221.22, 277.39]	[254.67, 316.77]
High income	$^{a}288.09_{a}$	$^{a}288.83_{a}$	$^{a}286.52_{a}$	$^{a}325.27_{a}$
	[257.28, 318.89]	[257.32, 320.34]	[255.26, 317.78]	[290.92, 359.62]
Low income	$^{b}235.11_{ab}$	$^{b}235.93_{ab}$	$^{b}227.07_{b}$	$^{b}263.84_{a}$
	[212.59, 257.62]	[213.64, 258.22]	[205.22, 248.92]	[239.33, 288.35]

StateDeg = Program run by State agency and enrollment priority to landowner with degraded land; StateHist = Program run by state agency and enrollment priority to landowner with historically managed land; NGODeg = Program run by NGO and enrollment priority to landowner with degraded land; NGOHist = Program run by NGO and enrollment priority to landowner with historically managed land; Significant differences between means of socio-economic characteristics are shown by superscript letters; Significant differences between means of policy designs are shown by subscript letters

2.4.4 Payment acceptance estimates

If the government plans to implement the prairie strips program and request the public for the monetary contribution, figure 2.5 gives what percentage of households will accept to pay at different payment options. When the government implements a program without any payment or $0 contribution, around 84% of the household with policies StateDeg, StateHist, and NGODeg accept that proposal. In the case of

NGOHist policy, about 82% of households accept the proposal without any payment from their side.

The percent of households to accept the payment options vary with payment options and policy designs. For example, if the government request to contribute $400 to implement the prairie strips program, 26.1 % of the households with NGOHist Policy will accept this proposal. The acceptance rate is 24.6% for StateHist policy, 24.1 % for StateDeg Policy, and 23.5 % for NGOHist policy. When the payment option is more than $90, the acceptance rate always remains high for households with the NGOHist policy compared to other policies. At the same time, households with NGODeg, StateDeg, and StateHist policy have almost a similar level of acceptance for all levels of payment.

If we assume a referendum to get public support to fund for prairie strips policy, it should get support from at least 50% of the households. To get that level of support, the maximum amount of payment the government can propose for public contribution can be $229.5 in the case of NGOHist policy. This amount for StateDeg policy should be $198, for StateHist policy should be $197, and for NGODeg policy should be $194.

2.5 Implications and discussion

The results from the current analysis support that people might prefer some policy to others, all else being equal (Ek et al., 2018). The higher willingness to pay for NGOHist policy might be because of the close ties of NGOs with both conserva-

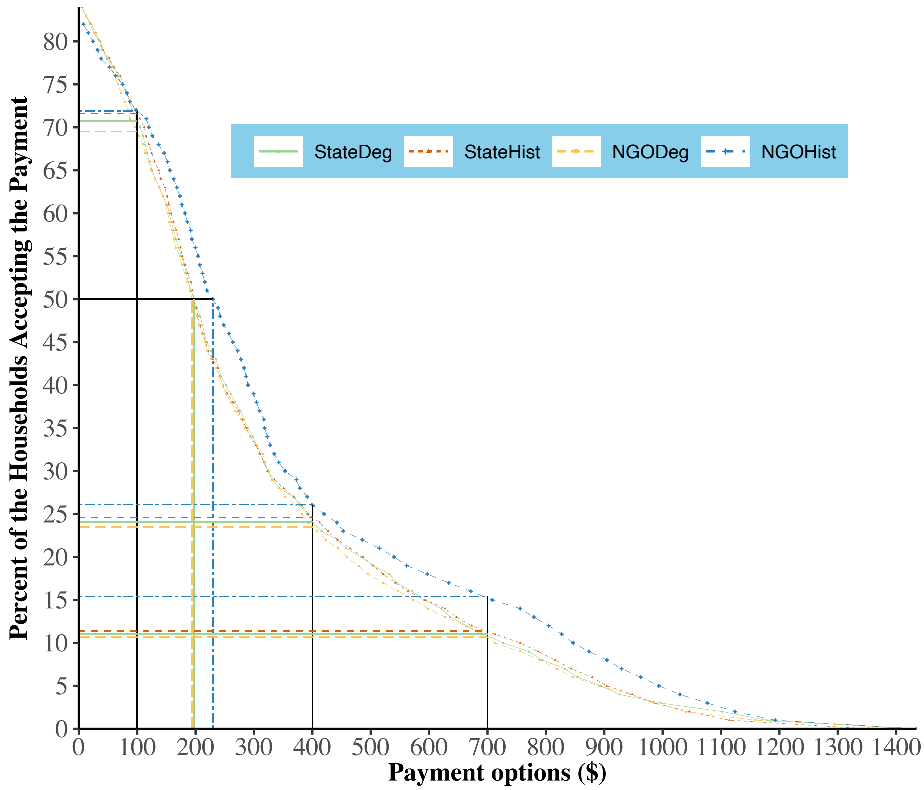

Figure 2.5: Percent of households that accept the monetary contribution for prairie strips at different levels of payment options- StateDeg = Program run by State agency and enrollment priority to landowner with degraded land; StateHist = Program run by state agency and enrollment priority to landowner with historically managed land; NGODeg = Program run by NGO and enrollment priority to landowner with degraded land; NGOHist = Program run by NGO and enrollment priority to landowner with historically managed land

tion practitioners and landowners, in addition to people's trust for past practitioners of good conservation stewardship. The efficient involvement in the CRP is contingent on solid partnerships between conservation practitioners and landowners (Lute et al., 2018) and NGOs can help in connecting them. The CRP registration process is complex, and practitioners spend more time leading landowners through enrollment and mid-contract management. Easy accessibility of landowners to NGOs can make the CRP registration process simple. As many NGOs have already integrated ecosystem services in conservation activities at the local level (Schaefer et al., 2015), people might have more trust for such NGOs in addition to enrolling past conservation practicing landowners. NGOHist policy, thus, can be sustainable because state or federal agencies fund and regulate, NGOs run, and landowners with good conservation stewardship enroll in such programs. The role of federal or state agencies will be in managing the public goods like land, water, ecosystem services, and enforcing environmental regulation (Schaefer et al., 2015)

Higher public valuation to water quality-related attribute in our estimate is similar to the finding by Arbuckle et al. (2015) that analyzes public perspectives for multiple-benefit agriculture in Iowa. This can be attributed to issue of water contamination by nitrate leach from agriculture field to water bodies in Iowa that increased cost of drinking water treatments. Des Moines Water Works (DMWW) filed a lawsuit against drainage districts in three upstream Iowa counties (Vedachalam et al., 2019). Although, the lawsuit was dismissed in federal court, it shows the underlying issues of excessive use of chemical fertilizers. Eventually, the role of prairie strips conservation practices in water quality and reduction in the cost of water treatment is one of the important benefits of prairie strips.

The socio-economic attribute in the valuation of ecosystem services is considered a research priority but less studied (Martín-López et al., 2012). Analyzing households socio-economic dimension of ecosystem services helps in designing policy for the specific target group. The relative importance of policy design vary between socio-economic groups of people in our analysis similar to reported by de Groot et al. (2010). We find high income respondent has significantly higher willingness to pay for ecosystem services attributes contrary to the findings from Dias and Belcher (2015) and Birol et al. (2006) and similar to Blasch and Farsi (2014).The respondents with higher education have a higher willingness to pay similar to Dias and Belcher (2015), Martín-López et al. (2012), and Birol et al. (2006) and opposite to Blasch and Farsi (2014). While Dias and Belcher (2015), Blasch and Farsi (2014),(Martín-López et al., 2012), and Birol et al. (2006) find age is defining factor for WTP and younger respondents have higher WTP, our finding do not support that. Our finding also supports gender does not affect on willingness to pay estimate, which is contrary to the finding from (Martín-López et al., 2012) that shows female value high for the ecosystem services of conservation management. Our study's finding supports that the prairie strips conservation is preferred by all irrespective of age group and gender of the respondents.

Two important observations in analyzing role of socioeconomic in WTP estimate are from income and education level of the respondents. We find individuals with high-education or high-income always significantly prefer new prairie strips management irrespective of the policies.

The willingness to pay estimated in this study has to interpret with few important considerations. First, the willingness to pay estimates here are likely to be upwards biased due to the hypothetical nature of ecosystem services realized from prairie strips (i.e., hypothetical bias). Second, as we reported before, the survey sample consists of more educated respondents than the actual population. Therefore, the willingness to pay estimated for alternative management scenarios of prairie strips are upper-bound values.

Finally, there are few things in the current study that can be a subject of study itself. First, the study assumes that respondents' choices do not vary whether they assume the prairie strips implementation is on either landlord or tenant. Ownership of land might have an impact on public willingness to pay for the conservation program. Similarly, public perception of the status quo is might affect their willingness to pay. Suppose no new policy or implementation measures are taken, especially in the case of climate change studies. Climate change will continue to increase from existing levels, hurting the environment. Therefore, more climate change might be accepted as the status quo by the public.

2.6 Conclusion

The conventional agricultural system in Iowa and upper Midwest, USA, has resulted in many negative consequences for multiple farmlands' ecosystem services. The prairie strips are designed to protect these services from environmentally sensitive land. Here we assessed how prairie strips' ecosystem services are valued and whether the public varies their value based on the policy designs of who runs the program and who is enrolled in the program. We quantified the marginal willingness to pay for ecosystem services attributes of prairie strips: decrease nutrient loss to water, decrease sediment loss, increase the number of pollinators, and increase types of birds in Iowa.

The willingness to pay for prairie strips' ecosystem service is positive for all assessed land management and enrollment policy with prairie strips. The marginal willingness to pay for ecosystem services is highest for decreasing nutrient loss to water, followed by decreased sediment loss, increased pollinators, and increased types of birds. The positive value of alternative specific constant confirms large numbers of respondents prefer new land management with prairie strips. Expanding prairie strips policy under a program run by NGO and enrollment priority to the landowner with historically managed land generated $286.11 one-time willingness to pay from Iowa households is significantly higher than other policy designs compared. Suppose the prairie strips program is run by NGO and enrolled to the historically managed landowner in the program. In that case, the government can propose a one-time public payment of around $230 to get the support of at least 50% of the households. This analysis suggests that investment in prairie strips via the CRP in Iowa is justified based upon the value of public and private benefits provided by CRP lands. The results suggest that public support considerably for prairie strips conservation practices, which ensures the sustainability of conservation programs.

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APPENDIX

A: Hausman Mac-Fadden test for Independent of Irrelevant Alternative

Models	Chi-squared test statistics	df	P-value	Subset of Choice Alternatives
1	19.677	6	0.003	(1,2)
2	19.01	6	0.004	(1,3)
3	11.083	6	0.085	(2,3)

B: Variance covariance matrix of random attributes with correlation coefficient from G-MNL model

	Decrease Nutrient Loss to Water	Decrease sediment loss	Increase number of pollinator	Increase types of birds	Alternative specific constant
Decrease Nutrient Loss to Water	† 0.218*** ‖ 0.056 § [1.000]	0.050*** 0.014 [0.887]	0.008** 0.003 [0.454]	0.039** 0.012 [0.517]	-4.365 3.352 [-0.142]
Decrease sediment loss		0.014** 0.005 [1.000]	0.002** 0.001 [0.536]	0.011*** 0.003 [0.569]	2.508 1.286 [0.317]
Increase number of pollinator			0.001** 0.000 [1.000]	0.005*** 0.001 [0.823]	0.554 0.323 [0.228]
Increase types of birds				0.025*** 0.008 [1.000]	2.657 1.405 [0.253]
Alternative specific constant					4331.6*** 847.18 [1.000]

*** p < 0.001, ** p < 0.01, * p < 0.05

† Diagonal elements are variance and off-diagonal elements are co-variance
‖ Standard error
§ Correlation coefficient

Chapter 3

THE IMPACT OF HETEROGENEOUS ATTITUDES AND EXPERIENCES ON WILLINGNESS TO PAY FOR FARMLAND CONSERVATION PROGRAMS

3.1 Introduction

The discrete choice modeling uses the standard random utility model (RUM), which assumes the indirect utility function measures the individual preferences (McFadden, 1974). The behavioral component of the choice process, such as individual knowledge, perception, and attitudes, are not prioritized in choice modeling for long in past (Daziano and Bolduc, 2013). Integrating individual behaviors, such as knowledge (Polydoropoulou, 1997; Ramming, 2001), and satisfaction (Polydoropoulou, 1997) in a choice model results in better performance of the model to explain the individual choices (Walker and Ben-Akiva, 2002). McFadden outlines how an individual's prior experiences affect memory, attitude, perceptions, preferences, and, finally, economic valuation in a choice process in his Nobel lecture (Mcfadden, 2001).

Choice modeling of farmland conservation preferences also can integrate individual behavioral aspects of respondents for better model performance. Principally, the public preferences for farmland conservation practices are affected by the ecosystem services of those practices. Conservation policies that do not recognize differences in preferences of the public, however, face a challenge to maintain a long-term sustainable program that needs support from larger and heterogeneous populations. Behavioral aspects like household experiences with farming and conservation practices and satisfaction with the current state of the environment can influence preferences and economic valuation of farmland conservation. Given the difference in public experiences and satisfaction, a crucial question for policymakers is how those differences affect preferences for farmland conservation and how much willingness to pay for those ecosystem services varies for that heterogeneous population.

The current study examines the roles of farm experience, conservation experience, and environmental satisfaction level on three key choices: (a) preferences for new farmland conservation practices, (b) relative preferences for the ecosystem services from farmland conservation; and (c) willingness to pay (WTP) for farmland conservation and ecosystem services. The current study, thus, helps to understand better the role and relative importance of these factors in explaining variation in preferences and willingness to pay for ecosystem services of farmland conservation.

Our study uses public preferences for a new farmland conservation program that provides funding to incorporate prairie strips into existing cropland. This practice was first added as a supported practice (CP-43) in the USDA-Conservation Reserve Program (CRP) in the December 2019 CRP sign-up. Prairie strips are perennial grass strips within row crop fields and are a tool to improve soil health, water quality, biodiversity, and erosion control (Schulte et al., 2017). However, there is a research gap in how households' experiences and environmental perceptions affect the economic value of those benefits.

Our study contributes to an emerging model of integrating individual behavior in policy design. Many papers exist on the relationship between socio-economic characteristics and preferences for farmland conservation. For example, researchers have explored the impact of income (Dias and Belcher, 2015; Birol et al., 2006), age (Dias and Belcher, 2015; Birol et al., 2006), gender (Martín-López et al., 2012), and education (Dias and Belcher, 2015; Birol et al., 2006) in preferences for ecosystem services (ES) from conservation practices. However, despite evidence that experiences and satisfaction are more helpful in defining preferences than socio-economic characteristics (Kaffashi et al., 2015), only a handful of researchers have examined how experiences and satisfaction levels can shape preferences and WTP. Understanding experiences is useful for policymakers to understand or explain the attitude and behavior of beneficiaries of a program (Han et al., 2018). For example, it helps to understand farmers' preferences where farmers are both providers and consumers of farmland ES and farmers should also share the cost of preserving farmland ES. Studies in the past also support that the WTP for farm conservation is different for a farmer than a non-farmer (Aregay et al., 2018), those with conservation experience relative to no experience (Beedell and Rehman, 1999; Daziano and Bolduc, 2013), and satisfaction with the existing environment relative to non-satisfied (Schilling et al., 2020) .

We conducted a web-based stated preference choice experiment survey for 1200 Iowa residents with four ES attributes and a one-time payment attribute. In this study, the four ES attributes are decreased nutrient loss to water, decreased sediment loss, increased number of pollinators, and increased types of birds. We also asked about the farming experiences, conservation experiences, and state of satisfaction about the environmental conditions in Iowa. A Random Utility Model framework is used to analyze the collected choice data using a Generalized Multinomial Logit Model (G-MNL) (Fiebig et al., 2010) in willingness to pay space model specification (Scarpa et al., 2008). We use an interaction model with ES attributes interacted with farming experience, conservation experience, and the environmental satisfaction index to estimate how WTP for ecosystem services varies with experience.

The current study shows that there is substantial WTP from the public for ES provided by prairie strips and that the WTP varies by ES and by attitudes and experience. The overall average WTP is a one-time payment of $241 at average measured values of ES. The WTP is highest for decreased nutrient loss to water relative to other ES. Higher farming experiences of households resulted in significantly higher preferences overall for new prairie strips conservation alternatives, while preferences for individual ecosystem services are not significantly different from those without farming experience. More experience in conservation resulted in significantly higher WTP for decreased nutrient loss to water. The level of households' satisfaction with the current state of the environment in Iowa is inversely related to WTP for four ecosystem services. Respondents satisfied with Iowas' existing farmland-related environment have a significantly lower WTP for prairie strips ES than those who are not satisfied.

3.2 Materials and Methods

3.2.1 Experimental design

Our study uses data collected in a stated choice survey of 1200 Iowa residents. The survey received IRB approval from the University of Nebraska in March 2019 and was implemented by the Dynata survey company in November and December of 2019. The sample consists of a pool of respondents with expressed willingness to participate in such studies with Dynata company (https://www.dynata.com/). A discrete choice experiment designed for our study has five attributes of prairie strips farmland conservation to define a choice alternative. Four of the attributes are ES, namely, decreased nutrient loss to water, decreased sediment loss, increased number of pollinators, and increased types of birds. The fifth attribute is a one-time household payment to expand the prairie strips program. Respondents are provided with information on each of these ES attributes before the actual choice question is asked.

Table 3.1 presents the attributes used, the definition of those attributes, and levels used for each of the attributes. Each ES attribute has three levels, and the payment attribute has four levels. Levels are chosen based on findings from a study of actual environmental outcomes after prairie strip adoption (Schulte et al., 2017) and after consultation with the Iowa State University STRIPS research team. Out of 324 (4×3^4) possible choice options, the fractional factorial design identified 36 non-trivial choice options.

Figure 3.1 provides a sample question from the study. Each choice question has three options. Option A and Option B are two of the identified non-trival choice options. Option C is always the status quo option, which includes no changes in existing ES and no new payment. The design of choice questions maintains high design efficiency, no dominance, level balance, and orthogonality. We use three blocks of six questions per block to avoid respondent fatigue. Each respondent, thus, is provided with six such questions, which are presented in a random order. The survey provided information to respondents about the ecosystem benefits of prairie strips. The choice questions were preceded by a description of the proposed program with the following text:

> *Proposed Expansion of Prairie Strips: With new revenue, implementation of prairie strips could be expanded to a substantially greater number of crop fields throughout the state to simultaneously meet farmland- and environmental-protection goals. If the results of this survey provide evidence that an expansion is supported by the majority of Iowa residents, it may be expanded. If the results of this survey show little support for the program, it will not be expanded. The proposed program would involve new tax dollars (the tax amount will depend on the program design most preferred by survey respondents). If implemented, then a one-time payment would be added to your 2020 state income tax. The new tax dollars collected would be placed into a special fund set up for the construction and maintenance of the project over 30 years. By law, no additional payments would be required.*

*Levels are based on a study Schulte-Moore et al., 2017 and expert consultation

Table 3.1: Summary of attributes, definition and levels used for each attribute

Attributes	Definition	Unit	Levels*
Decrease nutrient loss to water	Reduction in total phosphorus, total nitrogen, or nitrate-nitrogen concentrations	% less	50, 70, 90
Decrease sediment loss	Reduction in sediment loss (loss of topsoil with nutrients)	% less	55, 75, 95
Increase number of pollinators	Increase in pollinator abundance	times increase	2, 4, 6
Increase types of birds	Increase in bird species richness	% increase	50, 100,150
One time cost to you	Willingness to pay for ecosystem services by prairie strips [as one time tax]	$	25, 50, 100, 200

Q. Which policy choice option you would prefer among the following?

	Option A	Option B	Option C
Decrease Nutrient Loss to Water	90 % Less	50% Less	No change
Decrease Sediment Loss	95% Less	75% Less	No change
Increase Number of Pollinators	2 Times More	6 Times More	No change
Increase Types of Birds	100% More	150% More	No change
One-time Cost to You	$25	$200	$0
Your most Preferred Option	☐	☐	☐

Figure 3.1: Sample question in the stated preference choice experiment; individual respondent gets six such questions randomized in sequence of order

3.2.2 Socio-economic attributes of sample

Table 3.2 presents the distribution of socioeconomic and demographic characteristics of the respondents. It compares the sample distribution with the population distribution of Iowa. The sample and the Iowa population have similar distributions for age and income. There are few differences in the distribution of sample compared to population distribution. The number of female respondents is higher than male respondents. The proportion of respondents with a college degree or higher (40.1%) is higher than the proportion in the Iowa population (26.9%). Rural, towns, and small cities represented 64.8% of the respondents representing an area with a population less than 50,000, which is comparatively higher than 39.9 % of the Iowa rural population.

Table 3.2: Sample (n=1200) and Iowa population distribution by socioeconomic characteristics

Characteristics	**Sample (%)**	**Population(%)**
Age		
19-24	16.7	12.7
25-34	15.6	16.5
35-44	15.10	16.1
45-54	13.3	14.7
55-64	19	17.2
65+	19.8	22.8
Education		
No high school degree	2.3	7.8
High school degree or GED	20.5	30.8
Some college (including two year college or technical or trade school)	37.1	34.6
At least four-year college degree	40.1	26.9
Gender		
Male	42.1	49.3
Female	57.4	50.7
Other/prefer not to say	0.5	–
Income		
Below $25,000	19.3	17.6
$25,000- $49,999	24.3	22.6
$50,000-$74,999	20.1	19.5
$75,000-$99,999	14.5	14.1
$100,000-$149,999	13.5	15.8
Above $150,000	8.3	10.5
City type		
Rural		
Rural under 10000 residents	18.7	39.9
Town under 10,000 residents	23.1	
City between 10,000 and 49,999 residents	23.0	
Urban		
City between 50,000 and 99,999 residents	17.3	60.1
City with 100,000 or more residents	17.9	

3.2.3 Farming and conservation experience, and environmental satisfaction

Table 3.3 provides the questions that are used to create the farm experience, conservation experience, and environmental attitude indices of the respondents. The farm experience index (FarmExpIndex) measures farming and farm-related experiences, education, and involvement of the respondent. Respondents answered their experiences with living on a farm currently or in the past, education or training related to farming, members of the community supported agriculture groups, and buying food at farmers' markets. If someone has such experience, it is valued '1', and if not, it is coded as '0'. Thus, the greater the range of experience, the higher the value of the farm experience index. The value of the farm experience index ranges from 0 to 4 for a respondent.

The mean value of the farm experience index in our study is 1.77. About 47% of the respondents either live on a farm (now or in the past) or have close family or friends who farm. Over half (58%) of respondents buy food at farmers markets. Fewer respondents (16% and 10%, respectively) are members of a community supported agriculture (CSA) group or have formal education related to farming.

Table 3.3: Farm Experience, Conservation Experience, and Environmental Satisfaction Indices of Survey Respondents

Index (mean ± std dev)	Parameter	Values	Parameter mean ± std dev)
Farm experience index (1.77 ± 0.87)	- Currently live on a farm OR Lived on a farm OR visited a farm regularly OR Any of close family members or friends currently farm	Yes =1, No = 0	0.47 ± 0.49
	- Taken any formal education related to farming? (e.g., 4-H, FFA, university degree)		0.10 ± 0.30
	- Member of a community supported agriculture (CSA) group		0.16 ± 0.37
	- Buy food at farmers markets		0.58 ± 0.49
Conservation experience index (3.13 ± 2.02)	- Participated in any conservation projects, such as stream clean up, roadside litter removal, recycling, composting, or similar activities in the past 5 years	Yes =1, No = 0	0.18 ± 0.38
	- Belong to any conservation or environmental organizations (for example, county conservation board, soil and water conservation district, a watershed group, Pheasants Forever, The Nature Conservancy)		0.46 ±0.49
	- Taken any formal education or training related to natural resource conservation, management, or environmental studies		0.65 ± 0.47
	- Garden, either on your own land or on community land		0.15 ± 0.35
	- Participate in hunting		0.37 ± 0.48
	- Participate in fishing and/or boating		0.75 ± 0.43
	- Participate in hiking and or camping		0.19 ± 0.39
	- Ride ski or snowmobile in the winter		0.07 ± 0.24
	- Like to go birding or birdwatching		0.77 ± 0.42
Environmental satisfaction index (13.44 ± 3.69)	- Iowa's natural resources are in near pristine condition	Strongly agree =5, Agree =4, Neither agree nor disagree =3, Disagree =2, Strongly disagree=1	2.67 ±1.02
	- Fertilizer loss (e.g., nitrogen, phosphorus) from Iowa farmland has a negligible impact on environmental quality		2.09 ± 0.95
	- There is not much loss of soil from Iowa farmland due to water run-off		2.37 ± 1.06
	- Iowa farmland provides ample habitat for pollinators such as honeybees and wild bees		3.04 ± 1.12
	- Iowa farmland provides ample habitat for birds such as pheasants and other grassland species		3.28 ± 1.21

Note: Range of indexes: Farm Experience Index - 0 to 4; Conservation Experience Index - 0 to 9; Environmental Satisfaction Index - 5 to 25

The conservation experience index (ConsExpIndex) measures the level of conservation related education, involvement, and experiences of the respondents. Nine such conservation related experiences are asked. Those experiences include participation in conservation project, belong to conservation or environmental organization, formal education in conservation, experiences in gardening, experiences in hunting, experiences in fishing, experiences in hiking, experience in skiing, and participation in birding or birdwatching. As with the farm experience index, each indicator has a value of '1' if the respondent indicated 'yes' and '0' otherwise. The possible range of ConsExpIndex is, thus, 0 to 9. The mean value of ConsExpIndex is 3.13 and the standard deviation is 2.02. The experiences with the highest levels of participation by respondents include formal education or training in conservation (65%), participation in fishing and/or boating (75%) and birding and/or birdwatching (77%). Experiences with relatively low rates of participation include skiing or snowmobiling (7%), gardening (15%) and participation in conservation projects (18%).

The environmental satisfaction index (EnvtSatIndex) measures how satisfied a respondent is with the current quality of natural resources and the farmland related environment in Iowa. Each of these questions was asked using a Likert scale with responses ranging from strongly agree (value of '5') to strongly disagree (value of '1'). Respondents, thus, may have maximum of '25' to minimum of '5' for the index. Environmental satisfaction measures the ability of the current state of the environment of Iowa to meet the needs and expectations of the public (Ziegler et al., 2012). It assesses the performance of a farmland-related environment in Iowa. The mean value of EnvtSatIndex is 13.4 with a standard deviation of 3.69. While most of the average values are near the center of the distribution, the level of agreement is highest with the statement "Iowa farmland provides ample habitat for birds such as pheasants and other grassland species" (mean value 3.28). The level of agreement is lowest for the statement "Fertilizer loss (e.g., nitrogen, phosphorus) from Iowa farmland has a negligible impact on environmental quality" (mean value 2.09).

3.3 Empirical model

Our estimation is based on random utility model (McFadden, 1974). The indirect utility function U of individual n for alternative j in t choice scenarios is given by

$$U_{njt} = \beta_n \boldsymbol{X}_{njt} + \varepsilon_{njt} = \beta_n \boldsymbol{X}_{njt} + \varepsilon_{njt}/\sigma \tag{3.1}$$

Where β_n are coefficients of ES attributes vector ($\boldsymbol{X}_{njt}$) for individual respondents. The random utility model here assumes the scaling σ of idiosyncratic term ε_{njt} is same for all. The σ is normalized to 1 in the estimation to identify the model coefficient β_n.

A more recent development in random utility models is the generalized multinomial logit model (G-MNL) (Fiebig et al., 2010), which includes scaling parameters in the estimation with necessary adjustments. The empirical model in current study use the G-MNL model. If we include a scale parameter that is heterogeneous in the population (σ_n), the preferences of individual are explained by both taste heterogeneity (β_n) and scale heterogeneity (σ_n). We re-parameterized the GMNL model to separate the payment attribute (p) and its coefficient (α_n) from other ecosystem services attributes (Scarpa et al., 2008; Hensher and Greene, 2003). The vector $\boldsymbol{X}$ thus include both ES attributes and payment attributes while vector $\boldsymbol{x}$ includes only ES attributes only. When price coefficient α_n is normalized to be 1 as in equation 3.3 the model gives a WTP space specification, where $\beta_n^* = \beta_n/\alpha_n$ directly provides the vector of respondent-specific WTP estimates.

$$U_{njt} = \sigma_n \left(\beta_n \boldsymbol{x}_{njt} \ - \alpha_n p_{njt}\right) + \ \varepsilon_{njt} \ = \sigma_n \left[(\beta_n/\alpha_n)\boldsymbol{x}_{njt} - p_{njt}\right] + \ \varepsilon_{njt} \tag{3.2}$$

$$U_{njt} = \sigma_n \left[\beta_n^* \boldsymbol{x}_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.3}$$

Our estimation uses the random attributes interacted with three indices of farm experience, conservation experience, and environmental satisfaction. The random attributes are uncorrelated in the estimation as the assumption of correlated attributes increases the number of parameters in the model exponentially, resulting in the local conversion of the model. The WTP coefficients (β_n^*) has components of the fixed coefficient for ES attributes to represent the mean coefficient for all respondents (β^*), coefficients to represent heterogeneity of three indexes variables ($\boldsymbol{Z}$) in the mean coefficient (μ^*), and the respondent-specific deviation (η_n^*).

$$U_{njt} = \sigma_n \left[(\beta^* + \mu^* \boldsymbol{Z}_{njt} + \eta_{\mathrm{n}}^*)\boldsymbol{x}_{njt} - p_{njt}\right] + \varepsilon_{njt} \tag{3.4}$$

The full specification of our model in G-MNL form becomes:

$$\begin{aligned} U_{njt} = [\sigma_n(\beta^* + \mu_1^* \mathrm{FarmExpIndex}_{njt} + \mu_2^* \mathrm{EnvExpIndex}_{njt} + \mu_3^* \mathrm{EnvtSatIndex}_{njt}) + \\ [\gamma + \sigma_n(1-\gamma)] \ \eta_n^* \ ] \ \boldsymbol{x}_{njt} - \sigma_n p_{njt} + \varepsilon_{njt} \end{aligned} \tag{3.5}$$

The scaling factor σ_n is normalized with mean one and standard deviation τ; thus, the high value of τ indicates the presence of higher scale heterogeneity. The parameter γ is a weight that defines whether scaling σ_n is for both fixed coefficients β^* and individual deviation η_n or only β^*. If $\gamma = 1$, only β^* are scaled, and the model is called G-MNL-I. If $\gamma = 0$, η_n are also scaled, and the model is called G-MNL-II.

In addition to attributes of ES, the random parameter vector (β_n^*) also includes an alternative specific constant, the value of which gives preferences for alternatives of prairie strips compared to the status quo option that cannot be directly attributed to one of the four ES attributes. The entire vector (β_n^*) has a multivariate normal distribution. The alternative specific constant is also scaled in our model estimation.The model estimated thus is a full-scale model as suggested by Hess and Train (2017). The simulated maximum likelihood (MSL) method estimates the likelihood function of such G-MNL model.

The estimated model further finds the conditional distribution of marginal willingness to pay estimate for respondents using Bayes rule (Train, 2009). The conditional marginal WTP are the posterior means of respondent level parameters estimated. The MSL provide the unconditional estimates of the parameter vector for ES (β^*) as $g(\beta_n^*|\theta)$, where θ represents mean and standard deviation of multivariate normal distribution of estimated β^*. The Bayes' theorem is used to derive a respondent-specific conditional estimator $f(\beta_n^*|y_n, \boldsymbol{X}_n, \theta)$. The conditional estimate of means of ecosystem service attributes vector β_n^* with its parameters of distribution θ is estimated as conditional expectation $\mathrm{E}(\beta_n^*|y_n, \boldsymbol{X}_n, \theta)$ for respondent n in the sample as below

(Train, 2009).

$$
\begin{aligned}
\mathrm{E}(\beta_n^*|y_n, \boldsymbol{X}_n, \theta) &= \mathrm{E}(f(\beta_n^*|y_n, \boldsymbol{X}_n, \theta) \\
&= \mathrm{E}[\frac{f(y_n|\boldsymbol{X}_n, \beta_n^*)g(\beta_n^*|\theta)}{\int_{\beta_n^*} f(y_n|X_n, \beta_n^*)g(\beta_n^*|\theta)d\theta}] \\
&= \mathrm{E}[\frac{\int_{\beta_n^*} \beta_n^* f(y_n|\boldsymbol{X}_n, \beta_n^*)g(\beta_n|\theta)d\beta_n^*}{\int_{\beta_n^*} f(y_n|\boldsymbol{X}_n, \beta_n^*)g(\beta_n^*|\theta)d\beta_n^*}]
\end{aligned}
\tag{3.6}
$$

Where, $f(\beta_n^*|y_n, X_n, \theta)$ gives the distribution of the ES parameters β_n^* conditional on the observed sequence of choices $y_{nt} = \{y_{n1}, y_{n2}, \ldots, y_{nT}\}$ for individual n, and g($\beta_n^*|\theta$) is the unconditional distributions of parameters of ES. The conditional expectation of β_n^* gives the conditional mean of the distribution of ES attributes and alternative specific constant.

The simulator for conditional expectation in GMNL model is given by:

$$
\widetilde{\beta_n^*} = \ Est.\ E[\beta_n^*|y_n, \boldsymbol{X}_n, \theta] = \mathrm{E}\left[\frac{1/R\sum_{r=1}^{R} \widehat{\beta_{nr}^*}\Pi_t P(y_{nt}|\boldsymbol{X}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta})}{1/R\sum_{r=1}^{R} \Pi_t P(y_{nt}|\boldsymbol{X}_{nt}, \widehat{\beta_{nr}^*}, \widehat{\theta})}\right] \tag{3.7}
$$

Where $P(y_{nt}|\boldsymbol{X}_{nt}, \widehat{\beta_{nr}^*})$ represents the probability of observed sequence of choices y_{nt} conditioned on attributes $\boldsymbol{X}$, and individual n specific unconditional coefficients vector $\widehat{\beta_{nr}^*} = \beta^* + \eta_{nr}$ with 'r' random draw and their parameters $\widehat{\theta}$. The current study uses statistical programs R (4.0.3) “mlogit,” and “gmnl” packages for the data analysis (Team, 2021).

3.4 Results

3.4.1 Model estimation

Table 3.4 provides the result of generalized multinomial logit (G-MNL) model with interaction (equation 3.5) estimated. The total WTP includes two parts: an alternative specific constant (ASC) and the value of the expected ES benefits. The ASC is the portion of WTP that cannot be directly attributed to expected changes in the four ES included in the survey. It can be interpreted either as a general WTP to adopt a new conservation policy relative to the status quo (beyond the ES benefits included) or it could be based on the WTP for other expected benefits. The interaction of ES and the farm experience, conservation experience, and environmental attitude indices shows marginal willingness to pay for 1% change in ES attribute interacted with a single unit increase in value of those indexes.

The model fit parameters justify the use of the G-MNL model compared to Multinomial Logit Model (MNL). Hausman McFadden test finds no independence of irrelevant alternative (IIA) in our data (Appendix I). The McFadden pseudo-R-squared is 0.33 for the G-MNL model, indicating a relatively good fit for the G-MNL model. The log-likelihood value improved by 24.26% in the G-MNL model (-5346.50) compared to the MNL model (–7060.42). The likelihood of the G-MNL Model is significantly better than the Multinomial Logit Model in the likelihood ratio test (LR test). The G-MNL models' Akaike Information Criterion (AIC) (10767.16) and Bayesian Information Criterion (BIC) (11063.01) are also lower with the G-MNL model than with the MNL model.

Three of the four ES attributes have positive and statistically significant main effects while the main effect for increase in types of birds and the ASC are positive but not statistically significant. The sign of the interaction effects is generally consistent with our expectations. The environmental satisfaction index (EnvtSatIndex) has a negative and statistically significant effect on the WTP for all four of the ES attributes included. Intuitively, those individuals who have a higher level of satisfaction with current environmental conditions are WTP less money for a program that improves environmental outcomes. While not statistically significant in three of the four cases, the conservation experience index (ConsExpIndex) has a positive coefficient with all four ES attributes, indicating an overall higher WTP for improvements in environmental outcomes. Interestingly, the farm experience index is only significant in the interaction with alternative specific constant (ASC), showing a higher WTP for a new conservation program to implement prairie strips. After necessary adjustment with interacted coefficients, the average estimates of marginal willingness to pay for each attribute are presented in Table 3.5. For example, the WTP of \$3.24 for decrease nutrient loss to water has to adjust with values for attributes of 'Nu $\times$ FarmExpIndex,' 'Nu $\times$ ConsExpIndex,' and 'Nu $\times$ EnvtSatIndex' to get the marginal willingness to pay for decrease nutrient loss to water.

The significant standard deviation for random attributes suggested there is substantial taste heterogeneity among the respondents. With a significant value of scale parameter τ to be 2.36 with a standard error of 0.13, the model implied a substantial degree of scale heterogeneity in the data. The weighting parameter γ is -0.03. Our preference data, thus, is closer to the G-MNL-II model, where the variance of residual taste heterogeneity increased with scale.

Table 3.4: Estimates of Generalized Multinomial Logit Model (G-MNL)

	Mean		Std Dev	
	Estimate	Std. Error	Estimate	Std. Error
Decrease nutrient Loss to water (Nu)	3.24***	0.40	0.10***	0.09
Nu × FarmExpIndex	−0.05	0.12	0.05	0.05
Nu × ConsExpIndex	0.14*	0.05	0.17***	0.03
Nu × EnvtSatIndex	−0.19***	0.02	0.01	0.01
Decrease sediment Loss (Se)	0.68***	0.16	0.14*	0.07
Se × FarmExpIndex	0.06	0.04	0.10**	0.03
Se × ConsExpIndex	0.01	0.02	0.06***	0.02
Se × EnvtSatIndex	−0.05***	0.01	0.01	0.01
Increase number of pollinators (Po)	0.26***	0.04	0.03	0.01
Po × FarmExpIndex	−0.01	0.01	0.04***	0.01
Po × ConsExpIndex	0.01	0.01	0.00	0.01
Po × EnvtSatIndex	−0.01***	0.00	0.00	0.00
Increase types of birds (Ph)	0.23	0.14	0.13*	0.06
Ph × FarmExpIndex	0.04	0.04	0.07*	0.04
Ph × ConsExpIndex	0.02	0.01	0.04*	0.02
Ph × EnvtSatIndex	−0.03**	0.01	0.02***	0.00
Alternative specific constant (ASC)	66.10	43.75	133.40***	10.05
ASC × FarmExpIndex	29.37*	11.10	5.21	4.22
ASC × ConsExpIndex	−5.11	5.23	15.75***	2.00
ASC × EnvtSatIndex	1.03	2.67	10.28***	0.67
Scale parameter (τ)	2.36***	0.13		
Weighting parameter (γ)	−0.03***	0.00		
Model fit:				
Number of observations	7200.00			
Log-likelihood at zero (MNL)	−7910.00			
Log-likelihood at convergence (MNL)	−6797.10			
Log-likelihood at convergence (G-MNL)	−5340.60			
McFadden Pseudo-R^2	0.33			
Likelihood ratio $\chi^2(22)$ (MNL vs. G-MNL)	2913.10***			
Info. criterion: AIC for MNL model	13636.24			
Info. criterion: BIC for MNL model	13780.76			
Info. criterion: AIC for G-MNL model	10767.16			
Info. criterion: BIC for G-MNL model	11063.01			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

FarmExpIndex = Farm Experience Index; ConsExpIndex = Conservation Experience Index; EnvtSatIndex = environmental satisfaction index

3.4.2 Overall willingness to pay

Table 3.5 provides the conditional distribution of mean estimates of willingness to pay estimated using equation 3.7. The second column in the table gives the marginal WTP for a 1% change in the value of the ecosystem services attribute. The WTP is highest for decreased nutrient loss to water, followed by decreased sediment loss, increased number of pollinators, and increased types of birds. For a decrease in nutrient loss to water, the marginal willingness to pay is \$0.96. The marginal willingness to pay for decreased sediment loss is \$0.16, for an increase in the number of pollinators it is \$0.09, and for an increase in the types of birds it is \$0.01. The low marginal WTP for more types of birds may reflect the relatively high level of satisfaction households have with the amount of habitat available for bird species (see Table 3.3).

The third column of Table 3.5 lists the overall WTP estimate for incorporating prairie strips in 10% of environmentally sensitive farmland in Iowa. As the survey asked the households to value ecosystem services with a hypothetical scenario of including prairie strips in 10% of environmentally sensitive farmland, the estimation is assumed to represent proper population preference when used 10% of prairie strips. Results from Schulte et al. (2017) find that including prairie strips in 10% of the environmentally sensitive land in Iowa is associated with a 75% decrease in nutrient loss to water, 90% decrease in sediment loss, 300% increase in the number of pollinators, and 100% increase in types of birds. Of the ES attributes included, the overall WTP is highest for the associated reduction in nutrient loss (\$72.19), followed by the value of increased pollinators (\$27.76). The mean value of the ASC is \$125.58, a value that does not depend on changes in the listed ES. Overall, the average household-level WTP for all ES is \$241.13, with 84.4% of households having a positive WTP for a conservation program that increases the use of prairie strips in Iowa cropland.

Figure 3.2 shows the distribution of willingness to pay for each ES attribute, the ASC, and the overall WTP (all values are based on the estimated ecosystem benefits of enrolling 10% of cropland into prairie strips). The overall WTP distribution shown in Figure 3.2(f) shows that relatively small changes in the tax burden can lead to significant changes in the support for a new program. For example, the WTP for the individual at 60% percentile is $127, which increases to $260 for 70% percentile. The distribution measured this way gives an important policy implication that if policy-makers set a one-time tax of around $127, only 40% of the population will be ready to pay that amount.

The last column of table 3.5 indicates important information on preferences of ES and alternative of the new management of prairie strips. The percent of respondents having positive willingness to pay estimate is 74.4% for decrease nutrient loss to water, 71.3 % for decrease sediment loss, 84.8% for increase number of pollinators, and 53.5% for increase types of birds. 80.7% of households chose new management of prairie strips compared to the status quo, and almost 84.4 % of the respondent have overall positive willingness to pay in doing so. Our findings are comparable to those of Arbuckle et al. (2015), who interviewed Iowans about their preferences for multi-functional agriculture. They discover Iowa residents put the highest priority on water-related benefits. Respondents also rank increasing wildlife habitat, restoring wetlands, and restoring native prairie as high priorities.

Table 3.5: Marginal and overall willingness to pay (WTP) estimate for sample households

Attributes	Marginal WTP (2019 $)	WTP for 10% Prairie (2019 $)	Households with positive WTP (%)
Decrease nutrient loss to Water	0.96	72.19	74.4
Decrease sediment loss	0.16	14.67	71.3
Increase number of pollinators	0.09	27.76	84.8
Increase types of birds	0.01	0.91	53.5
Alternative specific constant	–	125.58	80.7
Overall WTP	–	241.13	84.4

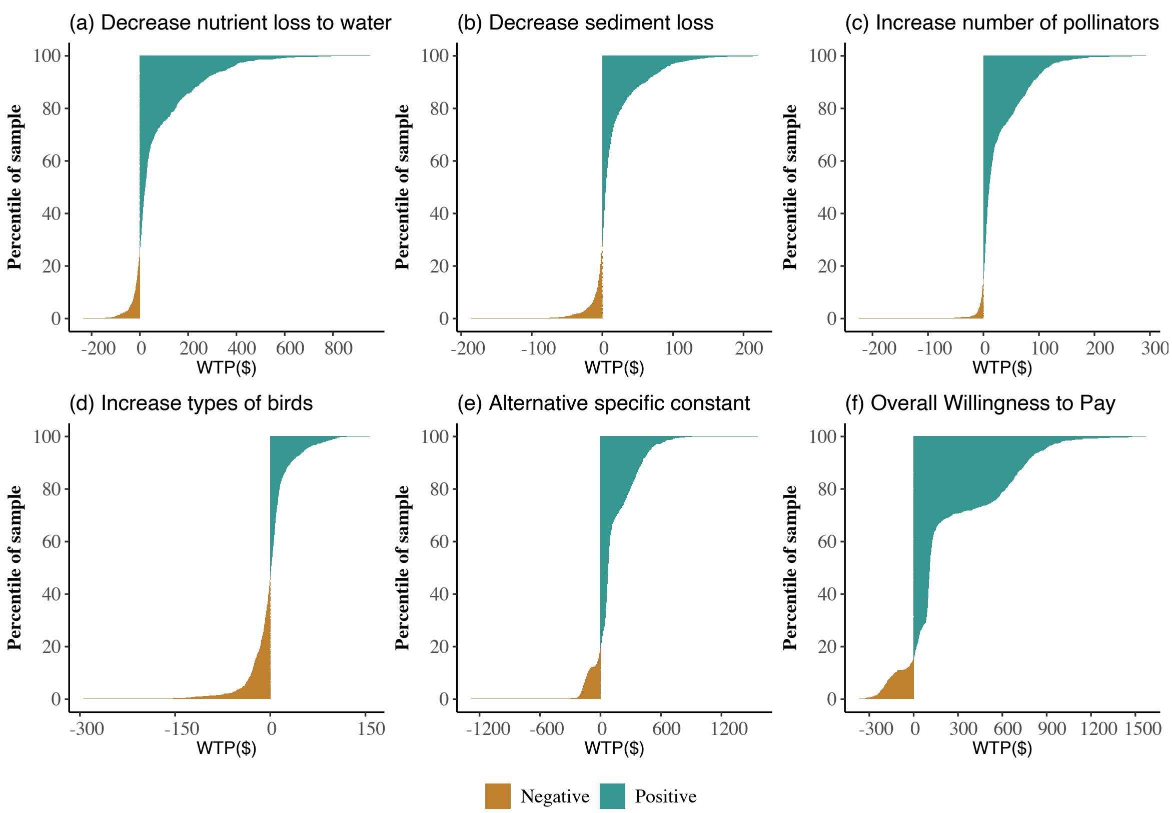

Figure 3.2: Distribution of willingness to pay for ecosystem services (a-d), alternative specific constant (e) , and overall program (f) for including 10% of prairie strips in environmental sensitive land

3.4.3 Role of experiences and satisfaction

Table 3.6 shows how the WTP varies for individuals with index levels at the 10% and 90% level of the index distribution. When we calculate the distribution of one index, the values of the remaining indices are at the actual level. The WTP estimates in table 3.6 are for including prairie strips in 10% of environmentally sensitive land of Iowa.

The individuals with different levels of FarmExpIndex have no significantly different WTP for those ecosystem services. The WTP for ES of prairie strips is positive at both 10% and 90% levels of FarmExpIndex except for increase types of birds at 10% level. There is a significant difference in WTP for individuals in the case of alternative specific constants. The less experienced have significantly lower WTP of \$88.06 than more experienced individuals with WTP of \$179.21. A significant positive value of ASC for more farm-experienced individuals shows that farmers are more convinced about the positive benefit of prairie strips. The overall willingness to pay for the individuals having a 10% level of FarmExpIndex is \$198.06 compared to \$300.43 for the individual having 90% level of FarmExpIndex.

In the case of 'ConsExpIndex,' individuals with less experience or 'ConsExpIndex' at 10% level have WTP of \$51.12 to decrease nutrient loss to water, which is significantly less than \$123.96 for individuals who have more conservation experience at 90% level of 'ConsExpIndex'. Conservationists are more concerned about leaching nutrients to the water than other attributes. The overall willingness to pay for the individual having a 10% level of ConsExpIndex is \$221.47 compared to \$286.93 for the individual having a 90% level of ConsExpIndex.

For 'EnvSatIndex,' the WTP is significantly different for all four ecosystem services attributes of prairie strips. The WTP is positive and significantly higher for individuals having lower satisfaction levels with existing farmland-related environmental status in Iowa. The negative WTP for the individual having a higher level of EnvSatIndex indicates those individuals prefer to be paid that amount to implement prairie strips conservation program as an alternative to the status quo. The individual at 10% of EnvSatIndex or those who strongly believe that there are issues of the environment in Iowa valued \$385.35 WTP compared to \$7.95 for those who are at 90% level of the index or who strongly believe that there are no such environmental issues. Finding from this indicates that individual perception about status of environment is one of the important factor in public valuation of conservation practices.

Table 3.6: Distribution of willingness to pay for ecosystem services of prairie strips planted in 10% of environmentally sensitive farmland for different levels of experience and satisfaction

	WTP with levels of FarmExpIndex (\$)		WTP with levels of ConsExpIndex (\$)		WTP with levels of EnvtSatIndex (\$)	
	10 %	90 %	10%	90 %	10 %	90 %
Decrease nutrient loss to water	77.22	64.94	51.12*	123.96*	160.66***	-69.05 ***
Decrease sediment loss	7.20	25.05	12.75	19.32	41.26***	-27.71***
Increase number of pollinators	29.80	23.96	23.86	37.16	51.03***	-9.38***
Increase types of birds	-4.22	8.26	-2.39	8.15	16.50**	-24.37 **
Alternative specific constant	88.06*	179.21*	136.13	98.34	115.89	138.46
Overall WTP	198.06	300.43	221.47	286.93	385.35	7.95

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; WTP = Willingness to pay; FarmExpIndex = Farm Experience Index (range: 0-4); ConsExpIndex = Conservation Experience Index (range: 0-9); EnvtSatIndex = environmental satisfaction index (range: 5-25)

3.5 Conclusions

This paper used a discrete choice experiment to value the ES provided by prairie strips, a practice that has recently been added as a supported practice under the USDA-Conservation Reserve Program. Public preferences are examined by focusing on four environmental attributes—decreasing nutrient loss to water, decreasing sediment loss, increasing pollinators, increasing types of birds, and one-time payment to the household as tax. The experiment also asked about individuals farming and conservation experiences and satisfaction levels with the current status of the environment in Iowa. The analysis uses a Generalized Multinomial Logit Model (G-MNL) that estimates the marginal willingness to pay for the ES attributes interacted with the respondents' attributes of farming and conservation experiences and environmental satisfaction level.

People are willing to pay a one-time payment of almost $241 for overall ecosystem services of prairie strips. The results indicate that the WTP is valued high for water quality than other ES pf prairie strips. There are significantly varied responses among households based on their farm and conservation experiences and environmental satisfaction level. An individual having higher farm experiences prefers the alternative of new prairie strips conservation. Having a higher conservation experience index resulted in higher WTP for decrease nutrient loss to water. Individuals not satisfied with the current status of the environment in Iowa valued significantly more to new farmland conservation policy of prairie strips. The overall economic valuation for ES showed sufficient economic support for enrolling more land in the prairie strips program in the future. The result from the current study provided important feedback to the policymakers as prairie strips is a new Conservation Reserve Program (CRP) started in December 2019.

There are few important considerations to make about the benefit calculated in this study. First, the level of attributes of ES for prairie strips for this study is based on research conducted on the experimental farm with expert supervision and is based on minimal field (experimental) data. These levels of ES could be overestimated for the normal farm field. Similarly, due to the hypothetical nature of ES realized from prairie strips (i.e., hypothetical bias), the total benefit estimated in our model could be upwards biased. Third, as we reported before, the survey sample consists of more educated respondents than the actual population. Therefore, the benefit generated by alternative prairie strips management should be considered the maximum value of the benefits.

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APPENDIX

A: Test of MNL model (unrestricted vs restricted)

	LR test	Wald Test	Hausman McFadden test for IIA(alt 1 and 2 only)
Statistics	9.1110	9.110210	-2561.9
p-value	0.0105	0.0104	1

Chapter 4

USING PRECISION CONSERVATION TO TARGET LAND RETIREMENT: INCORPORATING SPATIALLY VARIABLE PROFIT AND CROP INSURANCE PREMIUMS

4.1 Introduction

The US Farm Bill establishes voluntary conservation programs to encourage farmland retirement and the adoption of conservation practices on working lands (Sweikert and Gigliotti, 2019). The landowner gets incentives to remove less productive and environmentally sensitive fields for agricultural purposes and reestablish them in natural vegetation that meets the conservation objectives (McConnell and Burger, 2011). However, removing arable land from agriculture causes an opportunity cost in terms of revenue lost from crops that would otherwise have been produced.

Precision agriculture technology provides a powerful conservation planning tool for identifying environmental and economic opportunities in agricultural systems (McConnell et al., 2016). It provides agronomic information about farm production for better economic decisions (Bullock and Bullock, 2000). It also provides spatial information of different sub-fields that show the crop yield responses to inputs - this is beneficial for site-specific farm management (Trevisan et al., 2020). Appropriately used precision agriculture technology and yield monitoring data may result in higher economic and environmental sustainability (Basso and Antle, 2020). It finds the sections of a field that are less productive, more input-intensive, and less profitable. As a result, producers get better decision tools that decide where to grow a crop and where to retire for maximum farm profit.

Stull et al. (2004) first introduces the site-specific profitability analysis that uses precision agriculture information. They use global positioning system yield monitoring to identify field regions where the monetary benefits of conservation enrollment outweighed agriculture production. Barbour et al. (2007) extends the work of Stull et al. (2004) for 150 corn and soybean fields in Mississippi. They use spatial information to quantify the effects of adjacent plant communities on crop yield near field margins. McConnell and Burger (2011) use a similar principle of finding geospatial profit information to develop and test geospatial decision tool to optimize the dual objectives of environmental and economic benefits in the case of Habitat Buffers for Upland Birds practice (CP-33) under the continuous Conservation Reserve Program. Their geospatial decision support tools integrate as a part of the Arc GIS tool.

The decision framework introduced by Stull et al. (2004) and the decision tool introduced by McConnell and Burger (2011) has two major drawbacks in finding optimal land retirement for farmland conservation. First, they calculated net farm profit by subtracting production cost from total revenue but ignored possible heterogeneity in production cost within site. Precision agriculture technologies can identify less profitable areas, incorporating both yield and input use heterogeneity. Second, they omit the role of insurance when evaluating the benefits of targeted conservation. The site-specific yield information gives actual production history (APH), which is part of the crop insurance costs estimation. If we retire low-yielding crop areas with low APH, the insurance cost of remaining productive land decreases. This difference in insurance premium can lower overall cost and result in different sizes and sites of retirement for optimal farm profit based on the magnitude of change in insurance cost.

Thus, we propose a new decision framework that also incorporates site-specific insurance costs in addition to components of crop and land retirement for conservation reserve program (CRP) in farmland. The decision framework uses precision agriculture information and finds an optimal land retirement plan for CRP that provides maximum farmland profits. The findings from the framework give a location to retire and show whether it is profitable to retire yet all. Another application of the framework is to find the differences in the optimal retirement plan within different retirement strategies.

We used our decision framework to analyze land retirement decisions in 2019 for a new CRP-supported practice called prairie strip (CP-43) (USDA,2019) using data from an experimental corn plot in Effingham County, Illinois. Prairie strips are perennial grass strips within row crop fields and indirectly help improve water quality, soil quality, and biodiversity (Schulte et al., 2017). While the ecological benefit of prairie strips is known, the effects on the economic benefit for the farmers have not been analyzed extensively. Therefore, it is essential to evaluate net profit under different possible land retirement scenarios before making any investments. Retiring land for perennial grasses involves considerable upfront, and long-term capital outlays for establishment and management, and the revenue lost from crop areas may result in an economic loss (Tyndall et al., 2013). The optimization analysis helps farmers decide to retire site-specific land for prairie strips if done at the sub-field level. Landowners are also interested in such findings, as evident from a landowners survey in Iowa shows they are concerned about putting prairie strips in a strategic location within the field (Arbuckle, 2020).

The analysis uses profit optimization simulation for data from an on-site precision agriculture experimental plot. The mixed geographically weighted regression (GWR) (Brunsdon et al., 1996; Fotheringham, 1999) identifies the yield response function. The yield response function first finds the optimal inputs and output for the experimental unit(sub-plots), finding the optimal profit for sub-plots after that. The sub-plot in the harvester's swath is combined to form a strip, and there are 31 such parallel strips within the plot. The strips work as decision-making units for farmland conservation land retirement. The ecological benefits among the strips are assumed to be homogeneous. Therefore, differences in economic benefit are determining factors for land retirement decisions. The retirement plan consists of two sets of strategies. The first set of strategies have no crop insurance component and are Crop Only (COS), Retirement Only (ROS), and Crop and Retirement (CRS). The second set of strategies have crop insurance components in it and are Crop and Fixed Insurance (CFIS), Crop, Retirement, and Site-specific Insurance (CRSIS), and Crop, Retirement, and Fixed Insurance (CRFIS). The optimized profit information at strips level that includes insurance or not is used to make land retirement decisions for a crop with CRP and crop insurance.

The results from the current study estimate optimal land retirement plans for maximum profit from a given unit of the plot. When land retirement decisions are made based on crop and CRP land retirement profit without including crop insurance components, the optimal land retirement decision differs from when we include crop insurance components. The result also shows including site-specific insurance cost saves part of the insurance premium cost. Our estimation shows farmers can earn a total of 3.4% more profit if they use site-specific crop insurance premium costs in land retirement decisions.

The major contribution of the current study is to provide a new decision framework that provides an economic guideline to the farmers for decision-making in CRP land retirement. The decision framework provides a foundation for using agronomic information and knowledge of farmers to guide economic decision-making at the farmland level. The use of a new decision framework provides more economic gain to the farmers than existing decision tools while having similar environmental benefits. Incorporating site-specific crop insurance cost components in farmland decision frameworks has introduced new use of precision agriculture information in land use planning. As crop insurance is an integral part of most of the farmland in the US, most farmers can benefit if they use the new decision framework for land retirement decision-making. This framework is also applicable in the cases where the farmers retire their land other than conservation purposes.

4.2 Methods

4.2.1 Data

The current study uses the year 2019 data from a precision agriculture experimental plot of corn in Effingham County, Illinois. The plot had 1864 experimental units (sub-plots), out of which the experimental headlands and borders of the plot are discarded to remove global and spatial outliers (Trevisan et al., 2019). Thus, 1742 experimental units (sub-plots) are used for the current analysis. Each subplot has a dimension to fit the swath width of the harvester, and the width is equal to 40.1 ft. Thus, the area of each sub-plots is 1600.8 ft^2 resulting in a total area of 64.1 acres for the whole plot.

Variable-rate planters and fertilizer are used to apply seed and fertilizers in the plot. The variable rates of seed and N fertilizers are collected during crop planting and fertilizer application. Yield data are collected during harvest using combine yield monitoring systems. The ranges of variation for the tested rates of inputs are chosen according to the precision agriculture experiment objective for the plot. Other farming practices are kept constant throughout the plot and are conducted by the farmers by standard protocols for the region.

Figure 4.1 provides target seed rates, as-applied N rates, and as obtained yield rate from the experimental plot. Variable-rate applicators generally apply inputs with some degree of error, the monitors attached with the applicator can record the applied rates of inputs accurately. In the case of seed rates, the analysis uses experimental seed rates because of the unavailability of applied seed rates. The six experimental seed rates are 25, 29, 32, 35, 39, and 43 Kseeds acre^{-1}. In the case of nitrogen fertilizers, the analysis uses the as-applied rates, which range from 108.1 - 249.1 lb acre^{-1} with a mean of 183.1 lb acre^{-1}. The average yield of the crop was 134 bu acre^{-1} and ranged from 50 to 203 bu acre^{-1}.

Our estimation uses the crop budget reports of the University of Illinois Urbana-Champaign to get the output price and cost of the cultivation for corn planted after

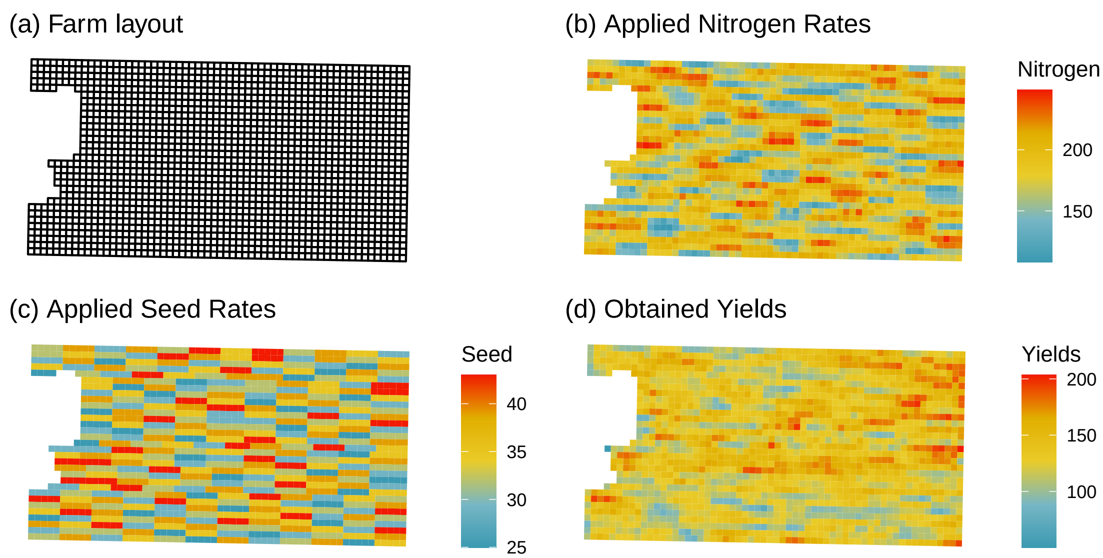

Figure 4.1: Yield, seed rates, and nitrogen rates in the precision agriculture experimental plot of corn

corn in Illinois. The cost of seed is \$3.2 Kseeds^{-1}, the cost of nitrogen fertilizer is \$0.38 lb^{-1} and the market price of the product (corn) is \$4.5 bu^{-1}. We grouped the costs of cultivation other than seed, nitrogen fertilizers, and crop insurance cost for the year 2019 as other costs (OC) in our estimation. Using the relevant crop budget report and excluding land rental cost, we estimate that OC is \$385.53 acre$^-$1. The Conservation Reserve Program (CRP) rental payment rate of continuous CRP in Effingham County, Illinois is \$164 acre^{-1} for the year 2019 according to USDA CRP record. The establishment cost for prairie strips CRP is \$30 per acre based on a finding from a study in Iowa (Tyndall et al., 2013).

The USDA risk management agency (RMA) website provides the crop insurance data for corn in Effingham county for the year 2019. The actuarial records and insurance premium calculation guidelines from USDA cost estimation calculate the crop insurance premium rate. The current study assumes revenue protection insurance and uses actuarial records for such insurance.

4.2.2 Yield response function

To identify the site-specific yield response function for the crop our analysis uses the experimental seed rates, as-applied nitrogen fertilizer rates, and observed yield of the corn. We use a mixed geographical weighted regression model (MGWR) that provides spatially varying relationships. The MGWR model has global and local explanatory variables that influence the response (Brunsdon et al., 1996; Hurvich et al., 1998).

$$y_i = \ \beta_{o(l_i,t_i)} + \sum_{j=1}^{q} \alpha_j X_{\text{ij}}(a) + \sum_{j=q+1}^{p} \beta_{j(l_i,t_i)} X_{\text{ij}}(b) + \varepsilon_\iota \tag{4.1}$$

where for observation at location i, y_i is the dependent variable, β_o is the intercept parameter at location$i$, (l_i, t_i) is the geographical location, $a(_1, \ldots, _q)$ are the q global coefficients and $\beta_1(l,t)...\beta_\text{p}(l,t)\}$ are the $(p$-$q)$ local coefficient.$x_{i1}(a)...x_{iq}(a)$ are the independent variables associated with global coefficients and $x_{i(q+1)}(b)...x_{ip}(b)$ are the independent variables associated with local coefficients, and ε_ι is the random error at location i.

The regression coefficients for global ($\boldsymbol{a}$) and local variables ($\boldsymbol{b}$) in MGWR are estimated as

$$\boldsymbol{a} = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{Y} \tag{4.2}$$

$$\boldsymbol{b}\left(l_i, t_i\right) = \left(\mathbf{X}'\mathbf{G}\left(l_i, t_i\right)\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{G}\left(l_i, t_i\right)\mathbf{Y} \tag{4.3}$$

Where, $G\left(l_i, t_i\right) = \text{diag } g_1\left(l_i, t_i\right),\ g_2\left(l_i, t_i\right)\ g_3\left(l_i, t_i\right) \ldots\ldots. g_n\left(l_i, t_i\right)$ is $n \times n$ diagonal weight matrix or spatial weight function. The spatial weight function $(G\left(l_i, t_i\right))$ will be a kernel function. We test two possible spatial kernel function and use the model with best fit function for this study. Gaussian spatial kernel function G_{ij} is continuous in nature and is given by

$$G_{ij}\left(l_i, t_i\right) = \exp\left(-0.5\left[\frac{d_{\mathrm{ij}}}{h}\right]^2\right) \tag{4.4}$$

Bi-square spatial kernel function G_{ij} is discrete in nature and is given by

$$G_{ij}\left(l_i, t_i\right) = \left\{\begin{matrix} \left[1 - \left(\frac{d_{\mathrm{ij}}}{h}\right)^2\right]^2 & d_{ij} < h \\ 0 & d_{ij} \geq h \end{matrix}\right\} \tag{4.5}$$

Where d_{ij} represents euclidean distance from spatial unit $(l_i,\, t_i)$ to $(l_j,\, t_j)$, and h is bandwidth. The calibration of spatial weight function finds the optimum bandwidth h in spatial weight function and we select the model that gives the lowest value of Akaike Information Criterion (AIC) (Hurvich et al., 1998).

Studies in past reports the yield response function of corn as a polynomial in nature (Trevisan et al., 2020; Bullock and Bullock, 2000). Our estimation uses a polynomial function of degree two as full model specification. When all variables in the yield response function are local, the model estimation is singular, and we could not estimate the model because of extreme multicollinearity. Our analysis, thus, uses a mixed geographically weighted regression (MGWR) model with some global and some local variables(Brunsdon et al., 1996; Hurvich et al., 1998). All the terms of interaction and higher-order are global variables in our model. Trevisan et al. (2020) find that the model's goodness of fit and interpretability increase with the MGWR model.

We test all the possible combinations of a polynomial function of the second degree to identify the appropriate yield response function (Appendix I). While testing shows the bi-square kernel density function fits better in terms of model fit criteria, it overestimates the optimized yield compared to real yield obtained in the experimental plot (53 to 203 bu acre^{-1}) (Appendix I). The problem of over-estimation of optimized yield also remains with the Gaussian kernel density function with full model specification. Thus, our estimation uses the following reduced form yield response function with adaptive Gaussian kernel density function, which both fits well with data and estimates optimized yield near to actual yield range for the plot. The bandwidth value (h) in the density function we use is 10, which shows data at subplot influences the density estimation of 10 nearest subplots.

$$Y_i = \beta_{0(i)} + \beta_{1(i)} S_i + \beta_{2(i)} N_i + \beta_3 S_i N_i + \beta_4 S_i^2 + \beta_5 N_i^2 + \varepsilon_i \tag{4.6}$$

Where, Y_i is yield, S_i is seed rates, and N_i is nitrogen fertilizers rate. $\beta_{0(i)}$, $\beta_{1(i)}$, and $\beta_{2(i)}$ are coefficients for local variables intercept, seed rates and N fertilizers rates, and β_3, β_4, and β_5 are coefficients for global variables of interaction of seed rates and fertilizer rates, square of seed rates, and square of N rates respectively.

4.2.3 Optimizing sub-plot profits

The site-specific yield response function provides optimum seed (S) and N fertilizers rates (N) using the site-specific net profit function (π_i). The yield response function uses identified optimal inputs to find the site-specific optimum yield. The optimization process identifies the site-specific optimal inputs (S_i^* and N_i^*) and outputs (Y_i^*). The optimal site-specific inputs ($S_i^*$and N_i^*) are

$$\begin{aligned}(S_i^*, N_i^*) &= \underset{(S,N)}{\operatorname{argmax}}[\pi_i(S_i, N_i)] \\ &= \underset{(S,N)}{\operatorname{argmax}}[P_y \times f\,(S,N) - W_S S - W_N \mathrm{N}\ - \mathrm{OC}\ ] \\ &= \underset{(S,N)}{\operatorname{argmax}}\{P_y \times (\beta_{0(i)} +\ \beta_{1(i)}\ S_i +\ \beta_{2(i)} N_i + \beta_3 S_i\ N_i + \beta_4 S_i^2 + \beta_5 N_i^2 +\ \varepsilon_i) - W_S S - W_N N\ - \mathrm{OC}\ )\}\end{aligned} \tag{4.7}$$

Where π_i is the site-specific expected net profit function, P_y, W_S, W_N, and OC are the price of corn, the price of seed, the price of N fertilizer, and all other costs and are assumed to be constant for the given year and crop.

The expected yield and profit under optimum site-specific management will be then $Y_i^* = f(S_I^*, N_I^*)$ and $\Pi_i^* = f(Y_i^*, S_I^*, N_I^*, P_y, W_S, W_N, OC)$ and are calculated as

$$Y_i^* = \beta_{0(i)} +\ \beta_{1(i)}\ S_i^* +\ \beta_{2(i)} N_i^* + \beta_3 S_i^*\ N_i^* + \beta_4 S_i^{*2} + \beta_5 N_i^{*2} +\ \varepsilon_i \tag{4.8}$$

$$\Pi_i^* = Y_i^* \; P_y - \; S_i^* \; W_S - N_i^* \; W_N - OC_i \tag{4.9}$$

4.2.4 Profit maximization from land retirement

The sub-plots along a single swath east-west represent a single strip. Thus, the entire plot is partitioned into 31 strips that are parallel to each other. There is heterogeneity within and across the strips in terms of input use, yield, and profit. However, for the economic analysis in our model, we analyze each strip as a separate a decision-making unit, and we use the average value of inputs, yield, and profits. We assume that each strip would be either fully cropped or fully retired from the production. The profit from crop only is compared with profit from retiring single strips to retiring the whole field. There are two possible optimization strategies for land retirement decisions. One is without crop insurance component, and another includes crop insurance.

Without Crop Insurance

The no-insurance land retirement strategy is to maximize net profit from two sources of income, crop and CRP rental payment. The crop plot is partially or fully under crop or CRP. We use the predicted site-specific crop yield with optimum inputs rates, site-specific optimum seed and nitrogen fertilizer rates, the market price of the product, input costs, CRP rental payment, and establishment cost of CRP to calculate revenue and cost for the given scenario at the field level. The net profit from the plot increases by strategically retiring less profitable crops as the CRP rental does not vary by the productivity of the land within the same plot. It results in higher net profit from a given land unit by retiring less profitable land for CRP rental payment and getting higher average profit from growing crops.

The net profit from plot accounts profit from crop field (crop profit) and retired field (CRP profit).The total profit from the plot is calculated as

$$\Pi_K^{Plot} = \underset{(\delta_1,\delta_2,\ldots,\delta_P)}{\text{Max}} \Bigg[\sum_{R=1}^{P} \Bigg((Y_R^*\ mp - \ S_R^*\ W_S - N_R^*\ W_N - OC_R) \times \ (1-\delta_R) \\ \times\ Area_R \ + \ \delta_R \times (\rho - \psi) \times Area_R \Bigg) \Bigg];\ \delta_R = (0,1); \forall K \tag{4.10}$$

s.t.,

$\sum_{R=1}^{P} \delta_R = K$, where K = numbers of strips to retire (0,1,. . .,31)

Retiring strips are contiguous

Π_K^{Plot} represents the maximum total profit from the plot after retiring K number of strips among a total of P strips. The value of K ranges from '0' to 'P', 0 representing no retirement, and P representing the whole retiring plot (i.e.,31 strips). The Y_i^*, S_i^*, and N_i^* represent optimized value for yield, seed rates, and nitrogen fertilizers, respectively. The market prices of output (corn), seeds, and nitrogen are represented by P_y, W_S, and W_N respectively. OC includes all other non-land costs except inputs (seeds and N fertilizers) and crop insurance premium. The ρ is CRP rental rate for corn, for the county of production, and year of production (2019), ψ accounts for all costs associated with the establishment of prairie strips.

There are three possible land retirement strategies when crop insurance is not included in the decision framework. When some strips are retired for CRP, and some strips are under crops, $\delta_R = 0$ for retired strips and $\delta_R = 1$ for strips with the crop. There are two sources of profit, profit from crop and profit from retirement as rental payment, and retirement plan is (a)"Crop and Retirement Strategy" (CRS). When no strips are retired, the $\delta_R = 0$ for all $(\delta_1, \ldots, \delta_P)$. Thus, profits are only from net crop revenue, and the retirement plan is (b) "Crop Only Strategy" (COS). When all strips are retired, the $\delta_R = 1$ for all $(\delta_1, \ldots, \delta_P)$. Thus, profits are all net profit of CRP rental payments, and retirement strategy is (c) "Retirement Only Strategy" (ROS).

With Crop Insurance

The crop insurance component in the profit maximization estimation of the plot has net profit/loss from three sources: crop, CRP rental payment, and crop insurance. Our estimation uses information for revenue protection insurance. When crop insurance is a separate component of profit analysis, farmers try to retire the location within the plot where insurance premium cost is high. The net profit/loss from the revenue insurance has two components, insurance premiums subtracted from indemnity payment and is given by

$$\begin{aligned} \Pi^{Insurance} = [\{&I(max\{hp, pp\} \times AY \times \tau > hp \times Yield) \\ &\times(max\{hp, pp\} \times AY \times \tau - hp \times Yield)\} \\ &-((pp \times AY \times \tau) \times PR \times (1 - \lambda(\tau)))] \end{aligned} \tag{4.11}$$

Where hp is the harvest price, and pp is the projected price of the output at the time of the insurance contract. τ represents the insurance coverage level and $(1 - \lambda(\tau))$ represents the subsidy level that is function of coverage level τ. PR is the premium rate, and AY is the approved actual production history (APH) yield of the crop. The indemnity payment in equation 4.11 triggers only when component $(hp/pp \times AY \times \tau)$ is greater than component $(hp \times \tau)$ and is given by differences of those two components. The Insurance premium cost comprises three components: liability, premium rate, and insurance subsidy. The liability is a product of the projected price, approved actual production history, and coverage level ($pp \times AY \times \tau$). The premium rate in revenue insurance is a function of rate yield (average yield of past ten years) and reference yield obtained by USDA actuarial data and other additional information.

As we have no information on the harvest price of the product, the information in equation 4.11 that triggers indemnity payment is not available. Given the yield records of the plot are from a single year, and no insurance coverage information for the plot is available, we made few reasonable assumptions for our estimation. First, the increase in indemnity payment can be equated to a decrease in premium cost with necessary adjustment. Adjusting premium cost according to yield records fulfills our objective of accounting for a variable insurance cost in the current analysis. However, suppose we have complete information about harvest price, projected price, actual AY, and actual insurance coverage level reported in the contract. In that case, this can easily be replaced with standard insurance profit calculation as in equation 4.11. For the estimation, we assume the average optimized yield for the whole plot as the mean AY ($\bar{AY}$) of the plot.

$$\bar{AY} = \frac{\sum_{R=1}^{P}(Y_R^* \times Area_R)}{\sum_{R=1}^{P} Area_R} \tag{4.12}$$

To obtain the AY of the retiring strips, we calculated adjusted AY ($\hat{AY}$). The adjusted AY is the average yield of the remaining strips other than the retiring strips. If P represents the total number of strips and we retire any K number of strips.

$$A\hat{Y}_K = \frac{\sum_{R=1}^{P} Y_R^* \times (1-\delta_R)}{\sum_{R=1}^{P} Area_R \times (1-\delta_R)};\ \delta_R = (0,1); \forall K \tag{4.13}$$

δ_R equals '1' if we retire a strip for CRP and '0' if we do not retire.

We assume the changes in revenue are due to a change in yield variation but not due to price changes because of the unavailability of price variation data. We adjust the coverage level such that it provides the same financial benefit as insuring the entire field at a coverage rate of 85%, as given by,

$$\hat{\tau_K} \times A\hat{Y}_K = \bar{AY} \times 0.85 \tag{4.14}$$

For example, if the mean AY for the plot ($\bar{AY}$) is 162 bu acre^{-1} and we guarantee revenue protection insurance at 85% of $A\bar{Y}_K$, the $A\bar{Y}_K \times 0.85$ is 137.7 bu. The value of τ_K ranges from 0.5 to 0.85. When the value of $A\hat{Y}_K$ increases after retiring less productive land, the value of $\hat{\tau_K}$ will decrease.

The equation 4.14 gives the coverage level $\hat{\tau_K}$ for the retiring K number of strips. As subsidy level is a function of coverage level and we assume a linear relation between them, the linear interpolation of coverage and subsidy level gives the subsidy level for identified coverage level.

The premium rate differs by crop insurance type to reflect the expected indemnity payments. The premium rate calculation corresponds to numerous factors and is much more complex than that of the liability. For simplicity to represent, we present the following way of writing the premium rate suggested by Mieno et al. (2018); however, a reader can look at the whole calculation procedure at the USDA RMA website (https://ewebapp.rma.usda.gov/apps/costestimator/Estimates/QuickEstimate.aspx, Accessed March 15, 2021). The statistical program R replicates the formula from the website and calculates premium payment under various AY levels, coverage rates, and subsidy levels for revenue protection insurance in our estimation.

$$\hat{PR}_K = f(\frac{rate\ yield_K}{reference\ yield}, D) \tag{4.15}$$

Where reference yield represents the expected county yield and D embodies all the other factors influencing premium rates. The ratio of rate yield to reference yield measures how much better the producer is relative to the average producer in the same county. In the simplest form, approved APH yield (AY) is identical with rate yield (RY) and is a simple average of 10 most recent records. Because we are using adjusted AY ($\hat{AY}$), the rate yield (RY) is assumed to be equal to $\hat{AY}$ in our analysis. As $\hat{AY}$ goes up, the ratio in equation 4.15 goes down, which in turn results in lower premium rates. Having information of $\hat{AY}$, we can calculate the premium rate using reference yield and other actuarial information for corn, rain-fed, Effingham County, Illinois for the year 2019 for each of the retiring strips.

The updated AY ($\hat{AY}_K$), adjusted coverage level($\hat{\tau_K}$) and interpolated subsidy level is used to calculate insurance premium cost. The premium cost adjusts the indemnity payment. If a strip has a lower AY that triggers the indemnity payment, insurance cost after adjusting AY, coverage, and premium rate are less for such strip. The following equation gives the profit from retiring prairie strips with crop insurance. The following profit equation has establishment cost of prairie strips subtracted from rental payment profit from retiring prairie strips.

$$\Pi_K^{Plot} = \underset{(\delta_1,\delta_2,\ldots,\delta_P)}{\text{Max}} \Bigg[\sum_{R=1}^{P} \Big((Y_R^*\, mp - \; S_R^*\, W_S - N_R^*\, W_N - OC_R) \times \; (1-\delta_R) \times \; Area_R$$
$$+ \; \delta_R \times (\rho - \psi) \times Area_R \Big) \tag{4.16}$$
$$-(pp \times A\hat{Y}_K \times \tau_{(A\hat{Y}_K)} \times PR_{(A\hat{Y}_K)} \times (1 - \lambda(\tau_{(A\hat{Y}_K)}))) \times \sum_{R=1}^{P} Area_R \times (1-\delta_R) \Bigg]; \; \delta_R = (0,1); \forall K$$

Where, $A\hat{Y}_K = \frac{\sum_{R=1}^{P} Y_R^* \times (1-\delta_R)}{\sum_{R=1}^{P} Area_R \times (1-\delta_R)}$

s.t.,

$\sum_{R=1}^{P} \delta_R =$ K , K = number of strips to retire (0,1,...,31)

Retiring strips are contiguous.

Where, $A\hat{Y}_K$ is the adjusted average historical yield (APH) as defined in equation 4.13. Both $\hat{\tau_K}$ and $\hat{\text{PR}}_K$ are function of $A\hat{Y}_K$ defined by equation 4.14 and 4.15.

The land retirement with crop insurance also has three retirement strategy. When $\delta_R = 0$ for some strips and $\delta_R = 1$ for some strips, the profits are accounted from three sources of income, crop, retirement, and crop insurance. If the crop insurance cost is calculated separately for non-retired (crop area) and site-specific (crop area-specific) insurance premium cost is used as in equation 4.16 the retirement strategy is (d) "Crop, Retirement, and Site-specific Insurance Strategy" (CRSIS). However, if insurance premium cost is calculated using average AY ($A\bar{Y}$) that replaces ($A\hat{Y}$) in equation 4.16, the retirement strategy is (e) "Crop, Retirement, and Fixed Insurance Strategy" (CRFIS). When there is no retirement i.e. $\delta_R = 0$ for all $(\delta_1, \ldots, \delta_P)$, all profits are from net crop revenue and crop insurance premium cost calculated using $(\bar{AY})$ for the entire plot and do not have CRP retirement component in equation 4.16, the retirement strategy is (f) "Crop and Fixed Insurance Strategy" (CIFS).

Suppose we retire the low productive land, the AY of the remaining land will be higher. Having higher AY results in a lower coverage level from equation 4.14 resulting in higher subsidies. The premium rate is directly related to the AY of the field. Having higher AY also decreases the premium rates so that landowners pay less for insurance premium (Mieno et al., 2018).

4.3 Results

4.3.1 Yield response function results

Figure 4.2 provides the distribution of coefficients for local variables in mixed geographically weighted regression model of specification defined in equation 4.6. The values of coefficient for intercept β_0 ranges from -106.27 to 284.78 that represents expected yield to vary by -106.27 to 284.78 bu acre^{-1} for different subplots in addition to that from other coefficients $\beta_1, \ldots, \beta_5$.

The values of β_1 and β_2 ranged from about -2.47 to 4.85 lb kseed acre^{-1} and -0.49 to 0.48 lb N acre^{-1}. If coefficients for all higher order and interaction variables (i.e. $\beta_3, \ldots, \beta_5$) are equal to '0' , β_1 and β_2 represents marginal expected product of *Kseed* and marginal expected product of N respectively. Marginal expected product of *Kseed* provides change in the expected yield in bu acre^{-1} when the seed rate is increased by 1.0 Kseed acre^{-1} whereas marginal expected product of N represents change in the expected yield in bu acre^{-1} when nitrogen rate is increased by 1.0 lb acre^{-1}.

The coefficients for global variables (i.e. β_2, β_3, and β_4) are 0.0111, -0.0389, and -0.0003 respectively. The global coefficients represents marginal expected product for SN, S^2, and N^2 respectively that gives change in expected yield in bu acre^{-1} of corn when value of these variables increased by 1.0 unit acre^{-1}.

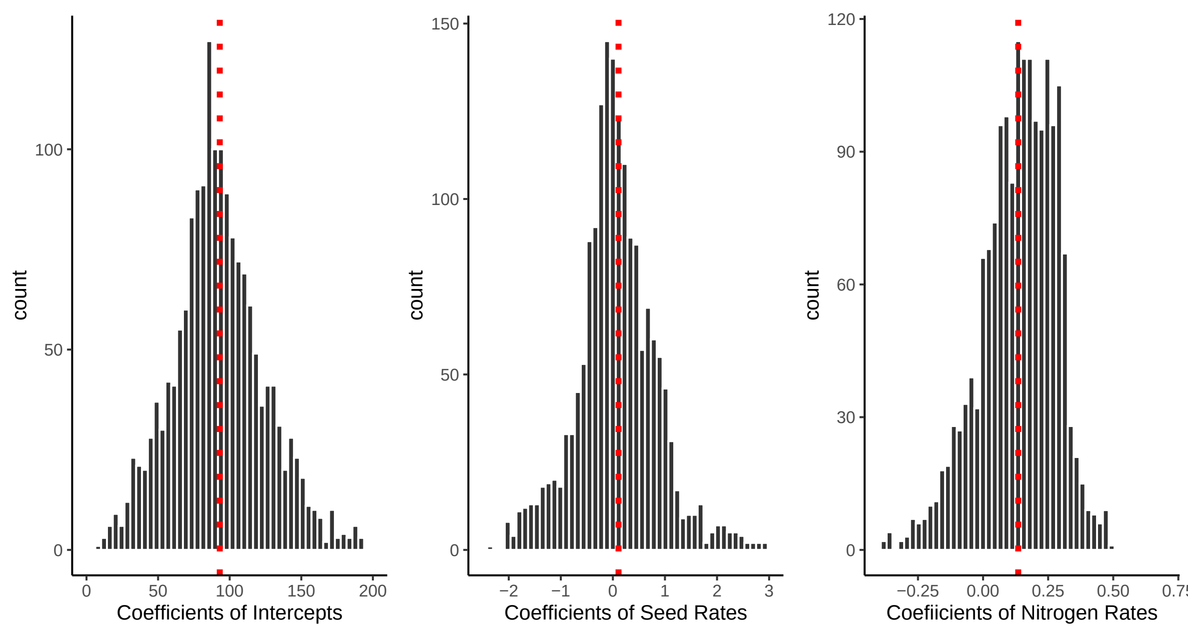

Figure 4.2: Frequency distribution of the fitted parameters of local yield response to (**a**) intercepts, (**b**) seed rates, and (**c**) nitrogen rates, in the on-farm precision experiments

4.3.2 Sub-plots profit maximization

Figure 4.3 gives the optimized seed and nitrogen rates, yield rates, and profits for the sub-plots analyzed. After estimating the yield response function, equation 4.7 provides the optimized seed and N rates for each subplot. To find the optimal S and N rates, we use a combination simulation of input cost and output prices that maximizes equation 4.7 with various seed rates and nitrogen rates. The possible range of seed rates and nitrogen fertilizer rates in the simulation are constrained within the actual minimum to maximum rates of those inputs applied in the precision agriculture experimental plot. Results show that a large number of optimized seed and nitrogen rates for subplots are at a corner solution. The optimized seed rates for most of the sub-plot are at the minimum possible seed rate while the optimized nitrogen fertilizer is mostly is at the maximum possible nitrogen rates.

The equation 4.8 estimates the optimized yield rates. The optimized yield varies from 117 to 221 bu acre^{-1}. Equation 4.9 estimates the optimized profit. In addition to that, optimized profit estimation includes information about the product's market price (P_y) and other non-land costs (OC) except fertilizer, seeds, and crop insurance costs. The values of the corn price and other costs are from a crop budget report published by the University of Illinois, Urbana Champion. It uses less productive central Illinois data, and other costs exclude the rental cost of land and crop insurance costs.

The subplots in a harvester's swath east-west in the plot are combined to form a strip to retire for the CRP. The values of optimized yield, costs, and profits are averaged from subplots within a strip to get the average values for a strip. When

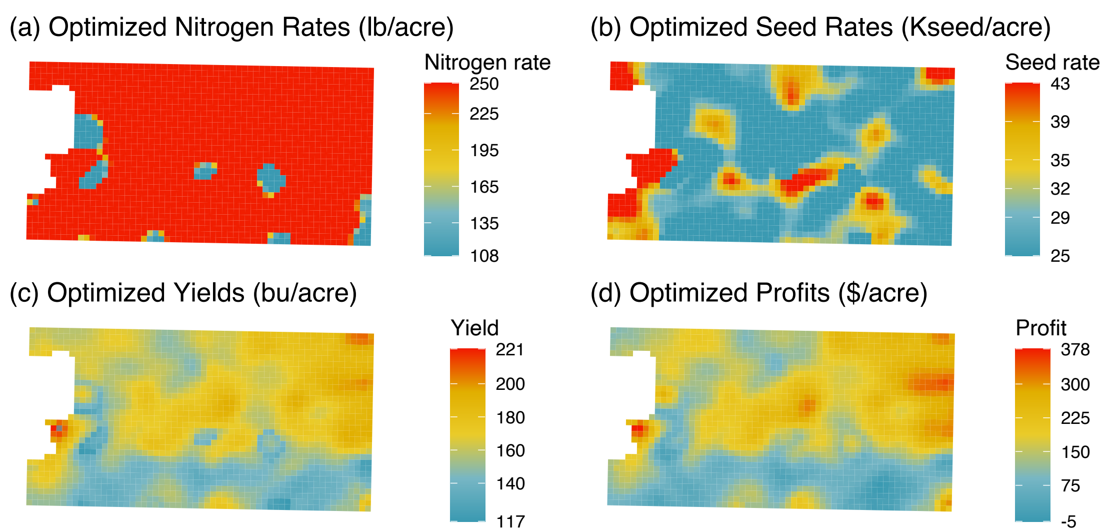

Figure 4.3: Optimized seed rates, nitrogen rates, yield, and net profits in the precision agriculture experimental plot of corn

the number of retiring strips is more than one contiguous strips, we use the weighted average values. Figure 4.4 shows the optimized yield and profit by strips (a single row of subplots). Our optimization at strip level shows on average, strip Ids higher than 20 are relatively less profitable than other strips. The role of input cost in net profit analysis is visible in strips ID 1-4 and 14-15. Strips 1-4 have relatively higher yields and higher costs, resulting in relatively lower profits. Similarly, Strips 14 and 15 have a relatively lower yield but higher per acre profit, which is also because of a relatively lower production cost in those strips.

4.3.3 Land retirement plans

The optimized values of profit at subplot levels are weighted averaged to find the optimized value at strips levels. Our plot has 31 such parallel strips. We analyze all

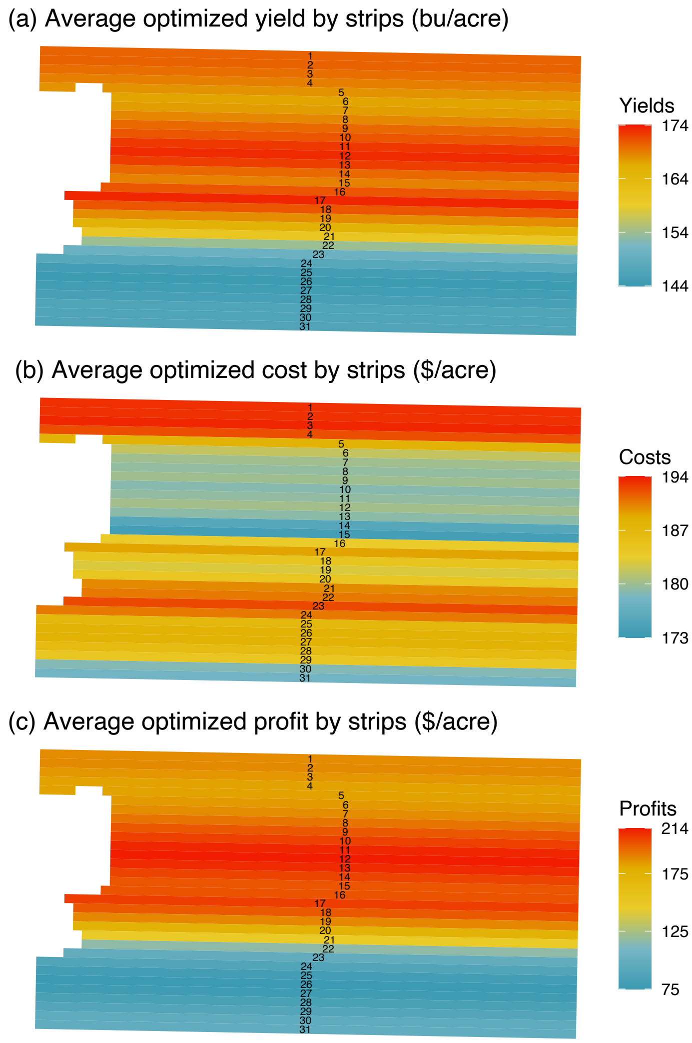

Figure 4.4: Optimized yield, costs, and net profits by strips in the precision agriculture experimental plot of corn; The numbers at the center of the strips represents the strip Id

possible combinations of contiguous strips with information on the area, yield, cost, and profits to decide on land retirement for CRP. The strips thus work as the smallest unit of decision-making for land retirement. The analysis of land retirement decisions results in 31 scenarios of retiring contiguous strips based on the number of strips to retire (K= 1 to 31). The most profitable plan for every 31 scenarios is the retiring plan for our analysis. For example, the results from a single strip retirement plan are in Appendix II. The retiring strip "26" is the most profitable case of retirement with a net profit of $140 when we do not account for the cost of insurance payment. Thus, the strip"26" is the one we chose for retirement when we have to retire the single strip. We analyze similarly for the remaining 30 scenarios that range from retiring two contiguous trips to retiring all strips (whole plot)

Figure 4.5 gives the per acre profit for retirement plans for CRP. The line graphs represent per acre profit for differences in retiring strategy. The per acre profit from three retirement strategies, "Crop Only Strategy" (COS), "Retirement Only Strategy" (ROS), and "Crop and Fixed Insurance Strategy" (CFIS), are constant. With ROS all land is retired, the landowner benefit per acre is $134 represented by point "o" in figure 4.5, which is the net profit from prairie strips CRP rental payment. It accounts for CRP rental payment for that land ($164) and establishment cost to prairie strips per acre ($30/acre). Similarly, when no land is retired, the landowner has different profits for a different retirement strategy. The per acre benefit with COS is $157.59 represented by point "a" in the figure 4.5, which accounts for benefits only from net crop revenue. When landowners no land is retired, and the whole crop area is with crop insurance, the retirement strategy is CIFS, where insurance premium cost calculation uses the average AY of the plot. The per acre profit with CIFS returns $119.36 given by point "b" in the figure 4.5. The horizontal lines represent these three constant land retirement strategies in figure 4.5 to compare with other land retirement strategies.

When retirement decisions are based on without crop insurance represented by CRS, retiring optimized strips retirement plan for 18 contiguous strips (strips group 14-31) represented by line segment AFK in figure 4.5 is profitable than COS ($157.59).

Thus, retiring at a maximum of approximately 60% of contiguous strips of the entire plot is profitable, beyond which (i.e., beyond point"n" retiring extra strip is loss compared to COS. With crop insurance strategies that include CRSIS and CRFIS, per acre profit is always higher from retiring than CIFS($119.36). However, retiring less than point "c" for CRSIS and less than point "d" for CRFIS in figure 4.5 is loss compared top retire whole plot for CRS.

If land retired with CRS strategy at optimal plan represented by point "e" in figure 4.5, the number of strips to retire (10) that accounts strips group 21-31 is less than the number of strips to retire with CRSIS or CRFIS (11) (i.e., 22-31 strips group). Our estimation shows the optimal retirement plan at point "j" or "k" in figure 4.5 with CRSIS or CRFIS identifies 37.14 % of land to retire compared to that of 33.98% for CRS (point "e").The retirement decision using CRSIS results in 0.64% (i.e., \$0.97 acre^{-1}) more profit than CRS strategy at point "f". Thus, if land retirement decisions do not consider crop insurance costs, we may lose the opportunity to get maximum profit. While CRSIS accounts site-specific yield records for calculating insurance premium cost, CRFIS takes the average yield of the plot for insurance premium calculation. If CRSIS is used for land retirement decisions, the per-acre profit is \$152.26 represented by point "j" in figure 4.5, which is 2.9% (i.e.,\$4.26) higher than CRFIS (point"k"). A decrease in insurance cost contributes the higher profits. At optimal land retirement plans with crop insurance, the premium cost are \$19.75 and \$24.02 only represented by line segments "hj" and "hk" for CRSIS and CRFIS respectively compared to \$38.23 for CIFS strategy (line segment "im").The use of site-specific insurance premium cost gives 3.46% more to the total profit (\$5.09 acre^{-}1) compared to if optimal retirement does not account for crop insurance and adds a fixed cost of insurance premium (given by point "g"). The vertical distance between point "g" and"j" gives the profit difference

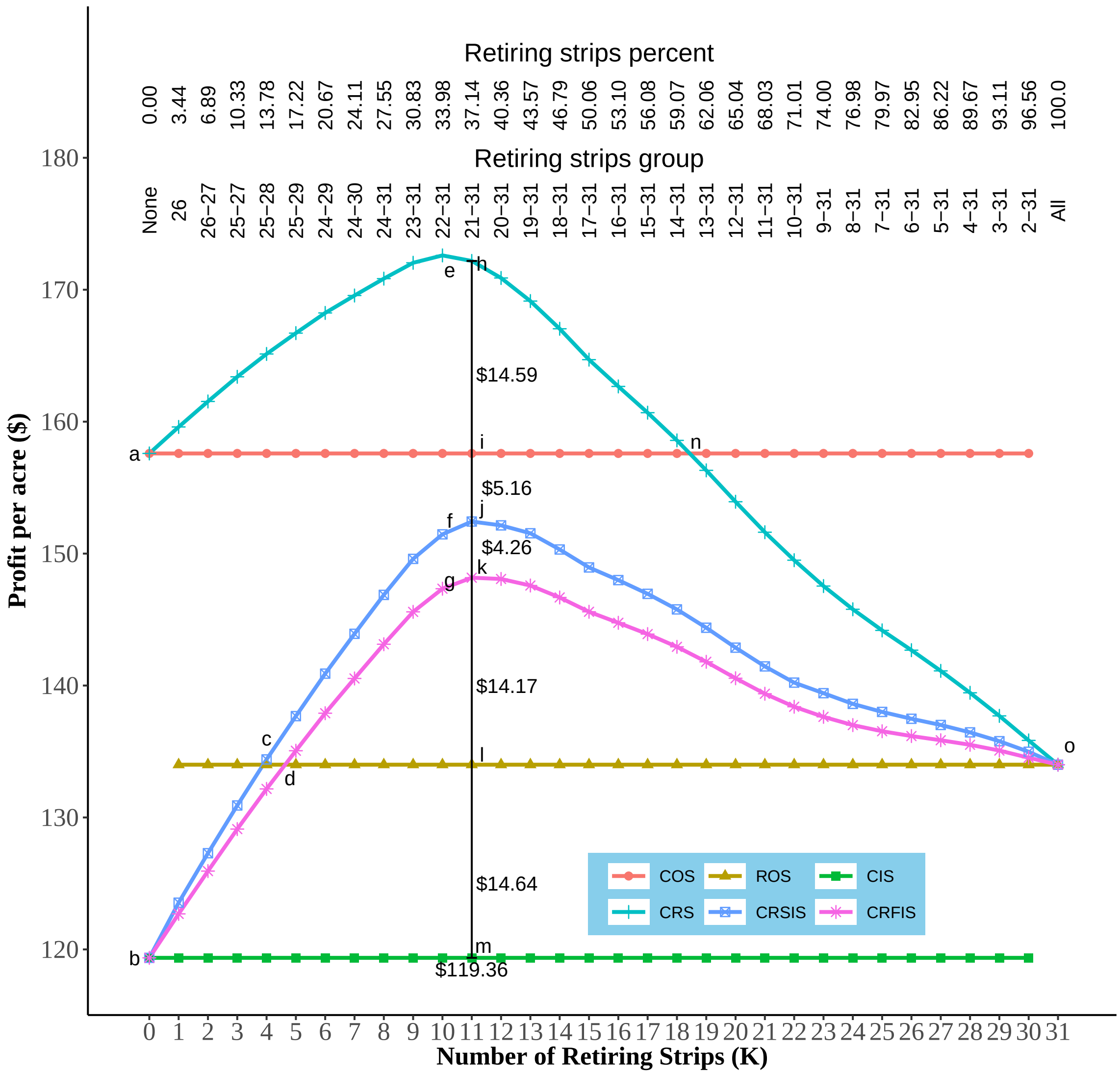

Figure 4.5: Per acre profit optimized with land retirement plans; COS = Crop Only Strategy , ROS = Retirement Only Strategy, CIFS = Crop and Fixed Insurance Strategy, CRS = Crop and Retirement Strategy, CRSIS = Crop, Retirement, and Site-specific Insurance Strategy, CRFIS = Crop, Retirement, and Fixed Insurance Strategy

between using site-specific insurance premium cost and fixed insurance premium cost.

When land retirement is less than the optimal plan (i.e., K < 11), the slope of per

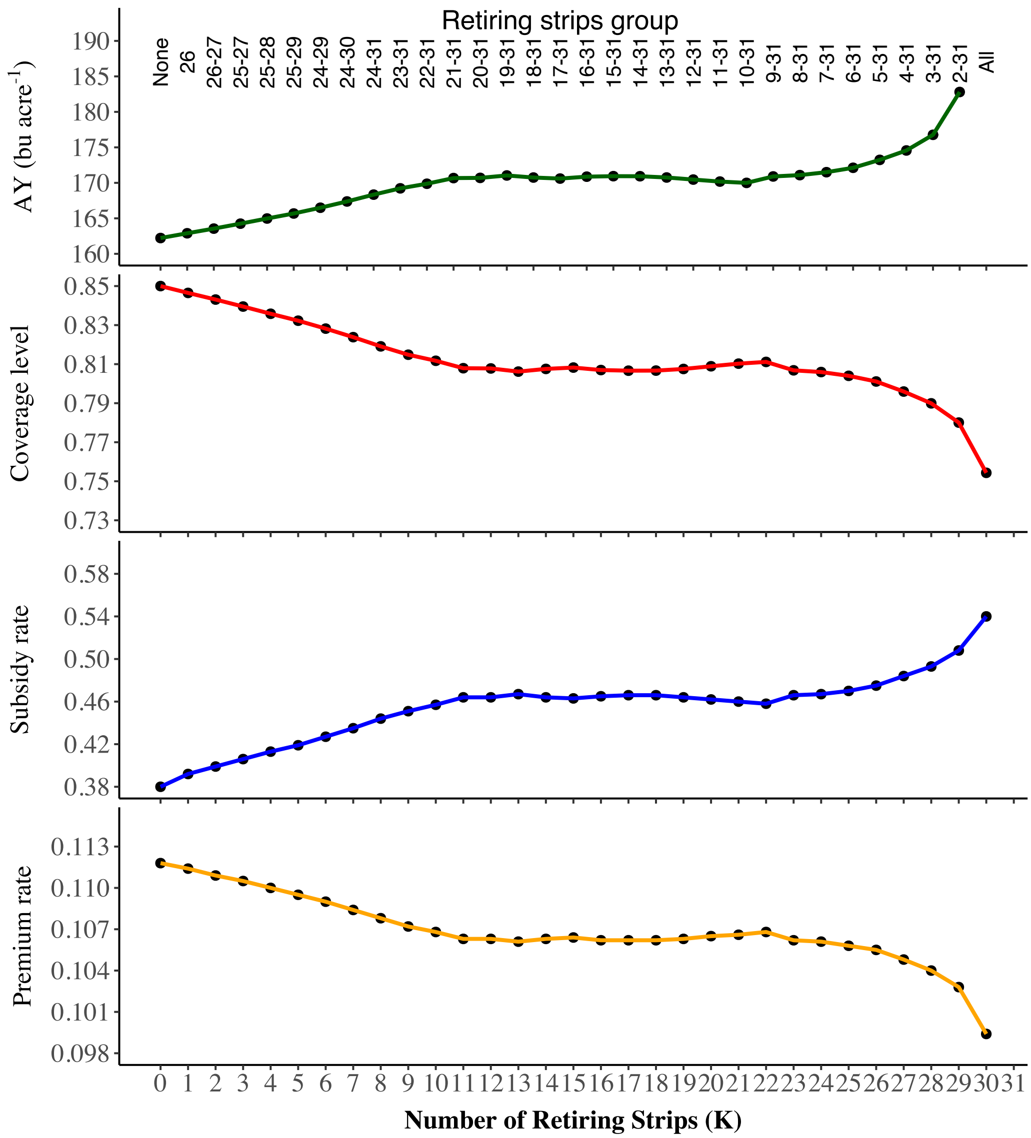

Figure 4.6: Relation between Approve APH(AY), insurance coverage, subsidy rate and premium rate, under different strips retirement plan; APH = Average Production History

acre profit line for retirement for CRSIS or CRFIS is higher than that with the CRS land retirement strategy. The opportunity cost gain by retiring more land for CRSIS or CRFIS is, thus, relatively higher than that for CRS. The rate of change of profit in a retiring plan with crop insurance, thus, is higher than without crop insurance. However, If land retired more than the optimal plan identified (i.e., K > 11), the profit line slope for CRS is higher than for CRSIS or CRFIS. The opportunity cost lost by retiring more land for the CRSIS or CRFIS, thus, is relatively lower than for CRS.

Figure 4.6 shows how the AY, coverage level, subsidy level, and premium rate change for different retirement plans. When AY increases, the insurance coverage level decreases. The subsidy is a function of coverage level and changes in the opposite direction to coverage, i.e., the higher the coverage level, the lower the subsidy rate. The premium rate is a function of AY. When AY increases, the premium rate decreases.

4.3.4 Prairie strips retirement plan

The land retirement decision also depends on retirement rules imposed by the program. The prairie strips practice establishes diverse perennial vegetation, oriented linearly within row crop fields. For example, with CRP, prairie strips may not exceed 25% of the cropland area per tract and range from 30-120 feet in width (USDA,2019).

Assuming every farm is unique in both the land type and the operational side, the policy wanted farmers to fit strips to address resource issues and operational constraints. There is not a mandatory distance for the gap between the strips in CP-43. The reason is two-fold. First, the policy assumes that farmers are willing to minimize the area in prairie strips because they want more land for crops. Second, USDA designed the policy to be as flexible as possible.

Figure 4.7 provides the retirement plan for prairie strips when the farmers retire

25% of the cropland. The strips to retire are strips group of 24-30 that account 24.11% of the entire plot. The retiring plots are contiguous in our plot. However, this could be any group of random plots that maximizes benefit from retirement within a plot. Retirement with site-specific insurance premium (CRSIS) results \$140.9 acre^{-1} net profit that is \$3 acre^{-1} more than that with fixed crop insurance premium (CRFIS).

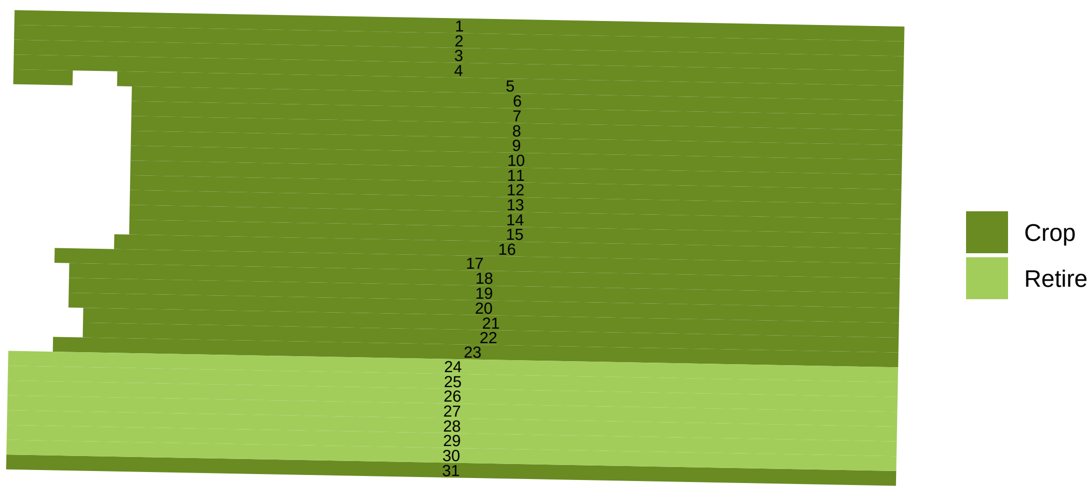

Figure 4.7: Optimal land retirement plan for prairie strips under the Conservation Reserve Program (CRP) guideline

4.4 Limitations

There are a few aspects to consider before drawing conclusions from the current study's findings. We introduced a new decision framework using the information from an experimental plot. There are many assumptions made to use the current decision framework. Those assumptions may not accurately reflect the real-world profit situation in the farmer's field.

First of all, we include insurance premium costs at the strip level rather than the sub-plot level in the analysis. As our net profit analysis uses two retirement strategies, both with and without crop insurance scenarios, strips level inclusion of premium costs ensures consistency of optimization in crop insurance scenario compared to without crop insurance scenario. If we use insurance information at the sub-plot optimization level, the optimized profit values might change slightly compared to what we have. However, it should not be significantly different than our current estimates for the net profit value.

Our analysis uses only one year of data from a single, because of that we adjusted approved APH, which in reality varies with actual data. Since actual indemnity payment or all information to measure insurance indemnity payment is unavailable, we estimated adjusted premium cost with adjusted approved APH yield (AY) of the plot. The indemnity payment will be different if complete historical yield data is available.

Similarly, our study examines land retirement decisions solely based on yield changes; however, crop price is also a deciding factor for total crop area (Miao et al., 2011). When crop insurance subsidies reduce, in general, the cropping area declines; however, our analysis does not account for the dynamic relationship caused by changes in product prices.

Another significant limitation is that it assumes environmental benefits are constant regardless of where we retire land for the strip in the plot. In many cases, that may not be a reasonable assumption. If benefits aren't constant, our framework can adjust to adapt, but we need to include spatial information on those benefits.

Finally, our estimate does not account for cost-sharing between the landowner and the tenant. We believed that farmers are the landowners and decision-makers for land use plans. However, if landowners are not the tenant themselves, the redistribution of benefits and expenses between landowner and tenant is determined by their land rent contract agreement. Furthermore, the decision to retire from land is dependent on who has the authority to make such a decision under their contract.

4.5 Conclusions

The primary objective of the current study is to develop a decision framework for optimal site-specific land retirement for conservation programs like CRP with and without considering site-specific crop insurance. Our analysis achieves that goal by using experimental precision agriculture plot information for corn in Effingham County, Illinois, in 2019. Site-specific optimization simulation uses information about seed rates, nitrogen fertilizers rates, crop insurance, grain yield, prices, and other costs.

The result suggests that the land retirement decision framework introduced here to incorporate a site-specific insurance premium cost can benefit the farmers in two ways. First, it provides maximum profit-gaining retirement decisions. If a land retirement decision does not consider crop insurance, the optimal land retirement might be less beneficial than a decision where crop insurance is an integral part. Second, it saves part of insurance premiums by providing site-specific insurance costs instead of fixed insurance costs. The use of site-specific insurance premium cost gives 3.46% more to the total profit (\$5.09 acre^{-1}) than optimal retirement that does not consider crop insurance cost and the cost of insurance work as a fixed cost. Given the prairie strips can retire a maximum of 25% of the plot, our results show that if we use the land retirement decision for the current experimental plot, farmers can benefit more by retiring strips groups 24-30 for the prairie strips.

We can apply this framework in several ways. Farmers can use this framework for land retirement for CRP, which economically benefits more without compromising environmental benefits. This framework also can be applicable for land retirement other than conservation purposes. The importance of this framework thus is more on educating farmers about this. If farmers are well informed about how the working land conservation program can be more beneficial, the enrollment in the program will increase. Thus, it can meet the dual objective of economic benefits to farmers and more conservation targets.

Finally, as the primary goal of this paper is to introduce the decision framework and complete information from the experimental plot is not available, our analysis makes many assumptions. Some of the assumptions are equality of rate yield and average actual production history yield (AY), using the adjusted AY instead of actual AY, assuming the price is less vital in defining indemnity payment and premium cost estimate. If complete and accurate plot information is available, the insurance component of the decision framework must be modified, which is a simple adjustment.

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APPENDIX

A: Selection of the yield response function

Model specification	R squared	AIC	RMSE	MAE	Optimized yield range (min,max)
	GWR Dist function: Gaussian				
$Y = f(S, N)$	0.719	13823	12.09	9.303	(176, 302)
$Y = f(S, N, \boldsymbol{SN})$	0.721	13810	12.05	9.302	(-15, 83)
$Y = f(S, N, \boldsymbol{S^2}, \boldsymbol{N^2})$	0.719	13817	12.07	9.303	(122, 214)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN})$ (**selected**)	0.722	13803	12.02	9.295	(117, 221)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN}, \mathbf{S^2N^2})$	0.721	13803	12.02	9.295	(114, 216)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN}, \mathbf{S^2N}, \mathbf{SN^2})$	0.722	13798	12.01	9.275	(218, 302)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN}, \mathbf{S^2N}, \mathbf{SN^2}, \mathbf{S^2N^2})$	0.722	13797	12.01	9.277	(3315, 3451)
	GWR Dist function: Bisquare				
$Y = f(S, N)$	0.927	12094	6.141	4.564	(106, 549)
$Y = f(S, N, \boldsymbol{SN})$	0.927	12090	6.134	4.564	(104, 544)
$Y = f(S, N, \boldsymbol{S^2}, \boldsymbol{N^2})$	0.928	12087	6.127	4.554	(106, 533)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN})$	0.928	12082	6.119	4.554	(104, 526)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN}, \mathbf{S^2N^2})$	0.928	12079	6.114	4.549	(101, 533)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN}, \mathbf{S^2N}, \mathbf{SN^2})$	0.929	12065	6.090	4.531	(112, 526)
$Y = f(S, N, \mathbf{S^2}, \mathbf{N^2}, \mathbf{SN}, \mathbf{S^2N}, \mathbf{SN^2}, \mathbf{S^2N^2})$	0.929	12063	6.087	4.526	(114, 550)
	Ordinary Least Square				
$Y = f(\mathbf{S,N,S2,N2,SN})$	0.321	15176	18.785	14.865	164

Note : Y= Yield, S = Seed Rates, N = Nitrogen rates, The variables bold in models represents fixed variables, and model with fixed variables represent mixed geographical weighted regression

B: Yield, APH, Coverage, Subsidy, Premium rates, and profits from retiring single strips with different retirement strategies

Strips	Yield (lb acre^{-1})	AY (lb acre^{-1})	Coverage	Subsidy	PR	**Net profit** $(\$\text{ acre}^{-1})$					
						COS	ROS	CRS	CFIS	CRSIS	CRFIS
1	170.294	161.968	0.850	0.380	0.112	157.590	134.000	155.740	119.360	118.860	118.830
2	170.354	161.965	0.850	0.380	0.112	157.590	134.000	155.730	119.360	118.850	118.820
3	169.769	161.986	0.850	0.380	0.112	157.590	134.000	155.840	119.360	118.950	118.930
4	168.879	162.018	0.850	0.380	0.112	157.590	134.000	155.930	119.360	119.030	119.020
5	167.879	162.091	0.850	0.380	0.112	157.590	134.000	156.020	119.360	119.080	119.050
6	166.980	162.093	0.850	0.380	0.112	157.590	134.000	156.090	119.360	119.040	119.000
7	167.343	162.082	0.850	0.380	0.112	157.590	134.000	155.990	119.360	118.940	118.900
8	168.482	162.047	0.850	0.380	0.112	157.590	134.000	155.820	119.360	118.750	118.730
9	170.042	161.999	0.850	0.380	0.112	157.590	134.000	155.630	119.360	118.560	118.540
10	171.014	161.969	0.850	0.380	0.112	157.590	134.000	155.470	119.360	118.400	118.380
11	172.503	161.923	0.850	0.380	0.112	157.590	134.000	155.280	119.360	118.230	118.190
12	173.205	161.902	0.850	0.380	0.112	157.590	134.000	155.210	119.360	118.160	118.120
13	172.202	161.933	0.850	0.380	0.112	157.590	134.000	155.310	119.360	118.260	118.220
14	170.086	161.998	0.850	0.380	0.112	157.590	134.000	155.490	119.360	118.420	118.400
15	168.873	162.035	0.850	0.380	0.112	157.590	134.000	155.600	119.360	118.530	118.510
16	171.051	161.867	0.850	0.380	0.112	157.590	134.000	155.560	119.360	118.520	118.470
17	173.418	161.904	0.850	0.380	0.112	157.590	134.000	155.240	119.360	118.310	118.270
18	171.040	161.824	0.850	0.380	0.112	157.590	134.000	155.490	119.360	118.520	118.460
19	168.199	161.918	0.850	0.380	0.112	157.590	134.000	155.840	119.360	118.850	118.810
20	165.378	162.012	0.850	0.380	0.112	157.590	134.000	156.300	119.360	119.290	119.270
21	160.603	162.266	0.850	0.386	0.112	157.590	134.000	157.170	119.360	120.500	120.140
22	153.902	162.484	0.849	0.388	0.112	157.590	134.000	158.140	119.360	121.660	121.110
23	150.044	162.694	0.848	0.390	0.112	157.590	134.000	158.790	119.360	122.520	121.820
24	147.645	162.776	0.847	0.391	0.111	157.590	134.000	159.170	119.360	123.040	122.260
25	145.021	162.869	0.847	0.392	0.111	157.590	134.000	159.450	119.360	123.380	122.540
26	144.274	162.896	0.846	0.392	0.111	157.590	134.000	159.600	119.360	123.540	122.690
27	144.778	162.878	0.847	0.392	0.111	157.590	134.000	159.520	119.360	123.460	122.610
28	145.713	162.845	0.847	0.392	0.111	157.590	134.000	159.320	119.360	123.240	122.410
29	146.612	162.813	0.847	0.391	0.111	157.590	134.000	159.120	119.360	123.010	122.210
30	146.646	162.811	0.847	0.391	0.111	157.590	134.000	158.910	119.360	122.810	122.000
31	146.717	162.809	0.847	0.391	0.111	157.590	134.000	158.870	119.360	122.760	121.960

Note: AY = Adjusted Approved Actual Production History (APH) yield, PR = Premium Rate, COS = Crop Only Strategy , ROS = Retirement Only Strategy, CIFS = Crop and Fixed Insurance Strategy, CRS = Crop and Retirement Strategy, CRSIS = Crop, Retirement, and Site-specific Insurance Strategy, CRFIS = Crop, Retirement, and Fixed Insurance Strategy

Chapter 5

FINAL REMARKS

"Essays on the Designs and Benefits of Land Conservation Programs" examines economic aspects of conservation practice in agricultural land called prairie strips. It uses two sources of information—first, a stated preference choice experiment data from a survey conducted with the public in Iowa. Second, a spatially variable data from a precision agriculture experimental farm in Illinois.

The first chapter investigates the impact of policy designs on individual household preferences for conservation practices of prairie strips on agricultural land. It measures Iowa residents' value on the ecosystem services (ES) provided by prairie strips and determines if that value changes under different policy designs. The policy design treatment varies in two aspects: who runs the program (state agency versus NGO) and who has enrollment priority (historically managed land versus degraded land). The willingness to pay (WTP) for ecosystem services is estimated using stated preferences from a choice experiment. Results indicate significant public support for expanding and funding the prairie strips program under all policy designs. WTP for the program is highest when it is managed by a non-governmental organization (NGO) and enrollment priority to the landowners who have historically managed land. Results for this policy design indicate a $286 one-time willingness to pay from households.

The second chapter measures the role of heterogeneous attitudes and experiences on willingness to pay for the farmland conservation program. It analyzes the role and relative importance of farming experiences, conservation experiences, and status of satisfaction toward the current status of the environment in explaining variation in preferences and willingness to pay for ecosystem services of prairie strips farmland conservation in Iowa. The stated preference data of prairie strips and its' ecosystem services attributes are collected using a stated preference discrete choice experiment. A willingness to pay space specification of the generalized multinomial logit model(G-MNL) is used to account for preference and scale heterogeneity. The results suggested that people are willing to pay for ecosystem benefits realized from the farmland conservation alternative of prairie strips. Almost 81% of households chose the alternative of prairie strips, and 84% of households have a positive willingness to do so. In addition, people are willing to pay a one-time payment of almost $241 for implementing prairie strips in environmentally sensitive land. The farm experiences, conservation experiences, and the environmental satisfaction level of households are significant to define varied preferences for ecosystem services (ES). Significant positive preferences for ecosystem services of prairie strips explain sufficient public support for enrolling more land in the prairie strips program in the future.

The last chapter examines the role of spatial variability of profit and crop insurance premium on site-specific land retirement decisions with an application to the Conservation Reserve Program (CRP). It introduces a new decision framework for determining optimum site-specific farmland retirement for conservation reserve programs (CRP) with or without crop insurance cost consideration. Profit maximization simulation using site-specific data from an experimental precision agriculture plot in Effingham County, Illinois, in 2019 achieves this. The simulation makes use of site-specific corn inputs and outputs from the experimental units (sub-plots). The harvester's swath's sub-plots are combined to form a strip. As a result, the experimental plot includes several parallel strips that function as land retirement decision-making units. Crop Only (COS), Retirement Only (ROS), Crop and Fixed Insurance (CFIS), Crop and Retirement (CRS), Crop, Retirement, and Site-specific Insurance (CRSIS), and Crop, Retirement, and Fixed Insurance (CRFI) are the six land retirement strategies compared in the current decision framework. The findings indicate that using site-specific insurance premium costs (CRSIS) benefits farmers by creating a different optimal land retirement plan with a higher net profit. It also reduces the expense of insurance premiums. As a result, if site-specific insurance costs are used in land retirement decisions, farmers will reap 3.4 percent more benefits than fixed insurance at the optimum land retirement decision. The new decision framework, thus, will advise farmers on the best location and size of farmland to enroll in CRP for a higher overall benefit.

The current research contributes significantly to the conservation practices of prairie strips. First, it helps policymakers know how the public economically values the prairie strips and their ecosystem services. How the differences in policy designs affect the willingness to pay an estimate of the public for ecosystem services of prairie strips is also important to know for successfully implementing the Conservation Reserve Program. In addition to that, current study feedback to the policymakers about the role of households farm and conservation experiences, and satisfaction level towards existing environment status. Second, this study is equally useful for farmers planning to retire their land for conservation practices like prairie strips partially. Farmers are informed most profitable land retirement site if they use the decision framework developed in the current study. The use of a new decision framework provides more economic gain to the farmers than existing decision tools while having similar environmental benefits