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Adoption Dynamics of Ecological Agriculture Practices: Understanding the Complementarity and Intensity in the US Midwest

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We investigate the complementarity and adoption intensity of ecological agriculture practices (EAPs) among Midwestern farmers, with a focus on environmental stewardship and profit-maximization motives. Using survey-level data on farmer characteristics in the US Midwest, we employ multivariate probit (MVP) and Poisson regressions to assess these linkages. The MVP results indicate that the degree of complementarity between EAPs varies in magnitude, with the highest complementarity between diversified crop rotation and integrated crop-livestock systems (50%). Regarding the adoption intensity, we find that farmers' decisions are influenced by both ecological and economic interests, with environmental stewardship motive playing a greater role.

Key words: Ecological Agriculture Practices, Adoption Intensity, Complementarity, Poisson Model, Midwest

Introduction

Today's agricultural sector faces a dual imperative—satisfying population-driven demand for food while simultaneously ensuring ecosystem integrity (Godfray et al., 2010; Foley et al., 2011; Lawler et al., 2014; Pretty et al., 2018). The use of conventional agriculture practices since the 1950s has had a cascading effect on both the environment and human welfare owing to intensive land use, monoculture, and heavy chemical use (Foley et al., 2011). In addition, adverse environmental problems such as water pollution, greenhouse gas emissions, biodiversity loss, and the decline in ecosystem services have become critical issues (Tilman et al., 2002; Turner et al., 2018). Between 1997 and 2011, global ecosystem services declined by an estimated USD 20 trillion annually, with future losses potentially reaching USD 51 trillion per year under current trajectories (Costanza et al., 2014). These losses are mainly caused by systems that fail to account for environmental and non-market values. In the US, this could result in a 23% decline in ecosystem service value (Kubiszewski et al., 2020).

Ecological agriculture practices (EAPs), such as cover crops (CC), conservation tillage (CT), diversified crop rotation (DCR), integrated crop-livestock systems (ICLS), and field edge (FE), offer a vital sustainable alternative to conventional industrial agriculture by focusing on long-term

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economic and environmental health and human well-being. In principle, EAPs aim to optimize resource use to boost economic returns while minimizing negative environmental impacts, strengthening system resilience, and promoting social equity (Wade, Claassen, and Wallander, 2015; Obembe, Wang, and Shew, 2023). EAPs provide wide-ranging benefits, including reduced soil degradation, mitigation of climate change by sequestering carbon, enhanced soil health, and improved water quality (Lal et al., 1998; Clay et al., 2012; Wade, Claassen, and Wallander, 2015).

Between fiscal years 2020 and 2024, roughly $31 billion was spent at the federal level on major conservation programs (USDA-ERS, 2025). Despite the billions in public investment, the adoption of ecological agriculture practices remains relatively low. Estimates from the Economic Research Service show that for corn and soybean farms in the US, CT is practiced on only about 19–25% of acres, no-till on 36–45%**,** and CC on just 8–11% of acreage. DCR adoption remains similarly limited on 22–24% of corn and soybean acres (Bowman et al., 2025).

The literature shows that the costs of some conservation practices can be a significant hurdle for farmers (e.g., Plastina et al., 2018; Wallander et al., 2021). For example, total costs for cover crop users per acre could be as much as $140 higher than for nonusers (Bowman et al., 2025). In addition, a riparian vegetative filter strip could cost, on average, $233 per acre per year (Tyndall and Bowman, 2016). However, some conservation practices may lower costs. For example, conservation tillage adopters in corn production incur lower total production costs compared with non-adopters ($598.82 vs. $625.35 per acre).

To promote the adoption of EAPs, policy efforts have thus far centered on government intervention, primarily through the provision of financial incentives and technical assistance, reflecting a classic view in the literature that farmer adoption decisions are driven largely by economic costs, expected profitability, and risk considerations (Cary and Wilkinson, 1997; Lichtenberg, 2004). This fits into a broader narrative about farmers' motivations to adopt agricultural technologies. Ryan, Kaplan, and Grese (2001), however, argued that the assumption of purely profit-maximizing behavior overlooks the heterogeneity among farmers, as some adopt practices driven by environmental stewardship. Extending this premise, Brodt et al. (2004) suggest that even farmers with profit-oriented motives may concurrently possess strong environmental stewardship values.

The literature also reveals that adoption has principally been studied from a dichotomous standpoint, adopters or non-adopters (e.g., Soule, Tegene, and Wiebe, 2000; Bergtold et al., 2012; Wang et al., 2019; Obembe, Wang, and Shew, 2023). A much narrower strand of the literature models adoption as a continuous (e.g., the proportion of land under a practice or years of use) or as the joint adoption of multiple practices (e.g., Pannell and Claassen, 2020; Gong, Bergtold, and Yeager, 2021; Thompson et al., 2021). For example, Thompson et al. (2021) investigated the adoption intensity of cover crops in Illinois, Indiana, and Iowa by measuring the number of acres planted. Gong, Bergtold, and Yeager (2021) also analyzed the adoption of three conservation practices (no-tillage, cover crops, and manure application) among Kansas farmers using a joint adoption framework. A common limitation across these studies is that they focus on measuring intensity within individual practices, such as acres, or on modeling joint adoption for a limited number of practices.

In the literature examining farmer motivations, Wang et al. (2019), in a study in the Northern Great Plains, explored whether adoption of soil conservation practices was driven by economic incentives or stewardship motives, the latter proxied by concern for soil health. However, their study employed a binary framework, omitting a more nuanced analysis of adoption intensity and the complementary use of multiple practices, thereby failing to capture the full extent of practice adoption. They focused on only a few ecological practices rather than examining a broader range.

This study introduces a novel approach by conceptualizing ecological practice adoption as a system-level decision, rather than a binary, single-practice outcome. We contribute by simultaneously examining the complementarities among a broader range of ecological practices (CT, CC, DCR, ICLS, and FE), which are often ignored in the conservation adoption literature, and exploring the intensity of adoption, defined as the number of ecological agriculture practices adopted. This approach provides a more comprehensive understanding of adoption dynamics in the US Midwest. We focus on these five practices because they are the most widely used in the region and promoted by the USDA Natural Resources Conservation Service (NRCS) and federal conservation programs such as Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP) for promoting soil health, water quality, and ecological intensification across US agricultural landscapes (USDA-ERS, 2025; Wade, Claassen, and Wallander, 2015).

Understanding the complementarity and intensity of conservation practices can be highly beneficial to both policymakers and farmers. For farmers, adopting multiple practices can lead to improvements in soil health, increased yields, and resilience to weather variability. For policymakers, our findings inform the design of bundled incentives, targeted outreach strategies, and cost-effective conservation program structures that can accelerate whole-farm ecological transitions.

This study uses survey data obtained from agricultural farmers in four US Midwest states as well as secondary data from various sources. The results indicate that all ecological practices investigated are complementary. However, the degree of complementarity varies in significance and magnitude. The highest complementary practices are DCR and ICLS (50%) and ICLS and FE (46%). In contrast, CT and ICLS practices have the lowest complementarity (11%). In terms of adoption intensity, the results indicate that farmers are motivated more by ecological credit motives (proxied by environmental stewardship) and the adaptive potential of agricultural methods than by profit-maximizing motives alone.

Methods

Survey Description

This study is based on a farmer survey we conducted in four US Midwest states: North Dakota, South Dakota, Minnesota, and Nebraska. Across the four states, we focused only on regions where corn and soybean production are predominant to ensure coverage of the major management practices pertinent to the region. In North and South Dakota, counties located east of the Missouri River were selected due to their predominance in cultivation, as counties in the West are typically involved in ranching. In Minnesota, we excluded the eastern counties, largely characterized by dairy farming and hay production. In Nebraska, we excluded the west and north central counties that have limited land suitable for crop cultivation purposes. In total, we covered 224 counties across four states.

We used a simple random sampling technique to select 1,500 farmers from each of the four states, for a total of 6,000 farmers. Farmers' mailing addresses were obtained from Dynata, a commercial data source that provides access to large-scale, high-quality sampling frames for survey research. The sampling frame was restricted to commercial farms that cultivate at least 100 acres of corn.

We conducted the survey between July and September 2021 using a modified version of the Dillman Tailored Design Method (Dillman et al., 2014), a recommended approach to maximize response rates in mail-based surveys. A four-phase mailing approach was used to contact survey respondents. In the initial stage, we sent an advance letter with a link to complete the questionnaire online, and a $2 note as a financial incentive. Subsequently, a paper copy of the survey and a prepaid return envelope were sent to non-respondents in the second wave. The third wave then included a reminder postcard, and the fourth wave included a second full paper delivery. Each wave targeted non-respondents from previous contacts. For duplicate responses from the same farmer, which is rare in this case and caused by the first response being received after we finalized the mailing list of the next wave, we retained the most complete response and used available information from the duplicate response to fill missing values where appropriate. The cumulative

Table 1. Comparison of survey responses with census and ERS data

	Age		Gender		Education		Cropland acres	
State	Survey	Censu	Survey	Census	Survey	ERS	Survey	Census
MN	59.4***	57.1	0.98***	0.69	72.1%	70.3%	894.4***	388.25
ND	56.7	56.8	0.97***	0.70	85.9%***	68.2%	2358.3**	1537.3
NE	59.1***	56.9	0.97***	0.67	74.2%**	66.9%	1079.3	988.7
SD	59.7**	57.2	0.99***	0.69	65.7%	63.5%	1550.6	1494.9

Notes: The values for age, gender, and cropland acres are based on the 2022 census of agriculture. The educational values are from the Economic Research Service for 2019-2023. The *, **, *** Indicates that our survey data are significantly different from census and ERS data at $p < 0.10$; $p < 0.05$; and $p < 0.01$ based on t-test. The average values for gender and education represent the mean for males and percentage of farmers who have advanced degrees (bachelor's degree and above).

response rates obtained after the four waves are 7.4%, 14.4%, 17.0%, and 20.4% respectively. After removing illegible samples due to bad addresses or respondent no longer farming, we have 5,473 eligible farmers in the sample. A total of 1,119 completed replies were returned, yielding a 20.4% response rate.

The representativeness of our survey sample is examined by comparing the survey data with USDA NASS census and Economic Research Service data using t-tests for age, gender, educational attainment, and cropland acres, as shown in Table 1. Except for North Dakota, the average ages of surveyed farmers in other states are significantly higher than the census averages. Our survey also reports no significant difference in higher educational attainment, except for Nebraska and North Dakota. With respect to cropland acres, survey farm sizes in Nebraska and South Dakota are not statistically different from census values. In terms of gender composition, however, the share of male operators in the survey is significantly higher than census values across all four states. The higher proportion of male operators in the survey likely reflects that respondents are typically principal farm decision-makers, who are predominantly male (USDA NASS, 2014). In contrast, census data includes both primary and secondary operators.

Data Description

The collected survey data include farm and farmer characteristics, and perception indicators, which were augmented by farm-level secondary data on soil and climate characteristics obtained from the Gridded Soil Survey Geographic Database (gSSURGO) and the Soil Survey Geographic Database (SSURGO) as described in Table 2.

Dependent Variables

Two dependent variables were chosen to capture the intensity of adoption and the complementarity of ecological practice adoption. The adoption intensity variable is a count variable ranging from 0 to 5, denoting the number of ecological agriculture practices adopted by a farmer. To examine the complementarity of practice adoption, we construct five dummy variables for each ecological agriculture practice, with one indicating adoption and zero otherwise.

Independent Variables

Farmers' motivations for adopting ecological practices are captured using two primary perception-based variables measured on 5-point Likert scale (1 = strongly disagree; 5 = strongly agree). The profit-maximization variable measures the extent to which a farmer prioritizes economic returns. The second variable is stewardship motivation, which captures farmers'

Table 2. Definitions and descriptive statistics of variables used in regression analysis

Variable	Definition	N	Mean	SD	Min	Max
Farm and farmer characteristics						
Age	Age of respondent (years)	1,050	58.74	12.96	20	95
Education	Highest education level (1 =high school or less; 2 = some college or technical school; 3 = four-year college degree; 4 = advanced degree)	1,066	2.09	0.83	1	4
Cropland acres	Total acres operated	1,088	1406.86	1598.41	12	16,000
Acres owned	Proportion of cropland acres owned	1,076	0.54	0.33	0	1
Off-farm income	Off-farm employment income (% of income from off-farm employment: 1 = <20%; 2 = 21 to 40%; 3 = 41 to 60%; 4 = 61 to 80%; 5 = > 81%)	1,061	2.12	1.38	1	5
Miles	Distance from largest field to the home (miles)	1,072	8.15	10.8	0	140
Farmer Perceptions						
Weather resilience	Conservation practices will help me better cope with extreme weather events (1= strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5= strongly agree)	1,061	3.9	0.85	1	5
Ecological credit	I am willing to trade short-term economic returns for longer-term ecological credits (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree)	1,058	3.22	0.84	1	5
Weather Frequency	Extreme weather events have become more frequent in my local area (1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree)	1,065	3.41	1.04	1	5
Profit-maximization	Farmers' primary task should be profit-maximization (1= strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree)	1,058	3.39	0.98	1	5
Soil, climatic factors and adoption						
LCC I & II	Proportion of land attributed to land capability class I and II (non-irrigated)	1,088	0.73	0.26	0	1
Temperature	The 30-year average temperature for the growing season (May-September) in degrees Celsius	1,089	25.05	1.42	21.83	28.76
Precipitation	The 30-year average precipitation for the growing season (May-September) in millimeters	1,089	452.5	60.79	329.31	589.12
Adoption	Adoption rate of the practices (0 – 5 practices)	1,089	2.63	1.47	0	5

willingness to forgo short-term profits in pursuit of long-term environmental benefits. These motivations are well-rooted in the adoption literature (e.g., Cary and Wilkinson, 1997; Chouinard et al., 2008), which has shown that economic and social stewardship ("warm glow") motives jointly affect adoption behavior.

To account for long-run climatic conditions, we add 30-year averages for precipitation measured in millimeters (mm) and temperature measured in degrees Celsius (°C) obtained from the Parameter-elevation Regressions on the Independent Slopes Model (PRISM, 2024). Prior studies (e.g., Arbuckle, Morton, and Hobbs, 2015; Wang et al., 2023) have shown that temperature and precipitation have significant effects on adoption. We also include extreme weather frequency to capture the perceived frequency of short-term weather risks.

We incorporate variables that capture the proportions of a farmer's operated land classified as Class I or Class II under the USDA land capability classification (LCC) system, referred to as LCC I & II. Class I soils have high natural fertility and few limitations for crop production, allowing for intensive cultivation with minimal conservation measures. Class II soils are also suitable for crops but have moderate limitations that require moderate conservation practices to maintain long-term productivity (Klingebiel and Montgomery, 1961). Due to higher land productivity, farmers operating a larger share of land under LCC I and II may be less inclined to adopt ecological practices that restore soil health, prioritizing productivity and crop yield maximization (Csikós and Tóth, 2023).

Regarding farm and farmer variables, we included factors such as education, cropland acres, acres owned, off-farm income, and the distance from the home to the largest farm. Education is a discrete measure with 1 – 4, ranging from 'high school or less' to 'advanced degree'. Several studies (e.g., Prokopy et al., 2008; Schimmelpfennig and Ebel, 2016) have demonstrated that education influences farmer adoption behaviors.

We include cropland acres and the proportion of acres owned to account for economies of scale and land-tenure effects on EAPs adoption. Farmers with larger farms often have lower per-unit implementation costs due to economies of scale, making them more likely to adopt ecological practices (Soule, Tegene, and Wiebe, 2000). We also include off-farm income, measured as the percentage of total income earned from off-farm sources, which has been shown to affect agricultural technology adoption (Fernandez-Cornejo, Hendricks, and Mishra, 2005).

We add state dummy variables for South Dakota, North Dakota, and Nebraska to account for regional heterogeneity in the study, with Minnesota as the reference category. We further include a distance variable defined as the distance from the farmer's residence to the largest operated field. This variable captures spatial and logistical constraints to EAP adoption, as longer distances increase travel and coordination efforts, which may lower farmers' management intensity (Rahman and Rahman, 2009).

Descriptive Statistics

Table 2 presents descriptive statistics for all variables used in the empirical analysis. Regarding farm and operator characteristics, the average farmer is about 59 years old and has at least some college education. The average operated cropland area is about 1,407 acres, and farmers own roughly 54% of the land they operate. The mean for off-farm income is 2.1, which means that on average, households derive 21 to 40% of their income from off-farm employment, indicating meaningful income diversification within the sample. The average distance between the farmer's residence and the largest operated field is 8 miles.

Regarding behavioral and perception-based variables, our results show that weather frequency has a mean of 3.4, indicating that, on average, farmers are neutral about the perception that extreme weather events have become more frequent. Regarding weather resilience, the mean of 4 indicates that, on average, farmers agree that ecological agriculture practices serve as

Table 3: Ecological practices adoption rate for the Midwest respondent in 2021

Variable	Definition	N	Freq	Rate (%)
Types of practice				
CT	Conservation tillage	1,089	821	75.4
CC	Cover crop	1,056	499	47.3
DCR	Diversified crop rotation	1,056	563	53.3
ICLS	Integrated crop and livestock management	1,047	471	45.0
Field edge	Field edge conservation management (buffer strips, windbreaks, etc.)	1,057	515	48.7
Adoption intensity				
Zero	Farmers who adopted none of the practices	1,089	91	8.36
One	Adopting only one practice	1,089	174	15.98
Two	Farmers who adopted two of the practices	1,089	251	23.05
Three	Respondent adopting three practices	1,089	235	21.58
Four	Respondent adopting four practices	1,089	202	18.55
Five	Farmers who adopted all the five practices	1,089	136	12.49

effective coping mechanisms. The means for ecological credit and profit-maximization are 3.2 and 3.4, respectively. This suggests that farmers have a neutral stance towards trading short-term economic returns for ecological credit and towards maximizing their profits. This dilemma has been observed in prior studies (e.g., Chouinard et al., 2008; Reimer, Thompson, and Prokopy, 2012). Regarding climatic and soil conditions, we found that about 73% of cropland is classified as LCC I and II. The average 30-year temperature and precipitation are 25.5 °C and 452.5 mm.

The average adoption rates of the ecological agriculture practices surveyed across the four states are presented in Figure 1. The map shows spatial variations in the adoption rates, which are typically higher (~ 58%) in counties along the eastern regions of North and South Dakota, southeastern Nebraska, and parts of western Minnesota, yet lower in central and eastern Minnesota and some parts of southern Nebraska, ranging from 20 to 35%. As shown in Table 3, farmers, on average, adopt approximately three EAPs. Only 8% of respondents report adopting none of the practices, whereas 13% report adopting all five. Adoption rates for CC (47%), FE (49%), and DCR (53%) fall within a moderate range, while CT is the most widely adopted practice, with a 75% adoption rate. Regarding adoption intensity, most farmers (23%) adopted only two practices out of the five, followed by those adopting three (22%) and four (19%).

We model farmers as rational decision-makers whose adoption decisions regarding EAPs are governed by both private net economic returns and broader ecological considerations. Farmers produce two outputs: marketable goods (crop yield) and non-marketable output (environmental externalities), using conventional system inputs (c) such as tillers, field cultivators, ecological system inputs (e) (e.g., no-till drills), and those for both production systems (w) including planters/seeders, tractors, manure/compost.

Let the farmer choose a vector of ecological practices $x = (x_1, \dots \dots x_5)$ for CT, CC, DCR, ICLS, and FE. The production function is specified in equation (1) as:

$$Y = f(c, e, w) \tag{1}$$

The marketable output (Y) is produced using conventional inputs (c), ecological inputs (e), and inputs for both systems (w). The production process involves total cost (C), which is comprised of the variable cost and fixed cost as specified:

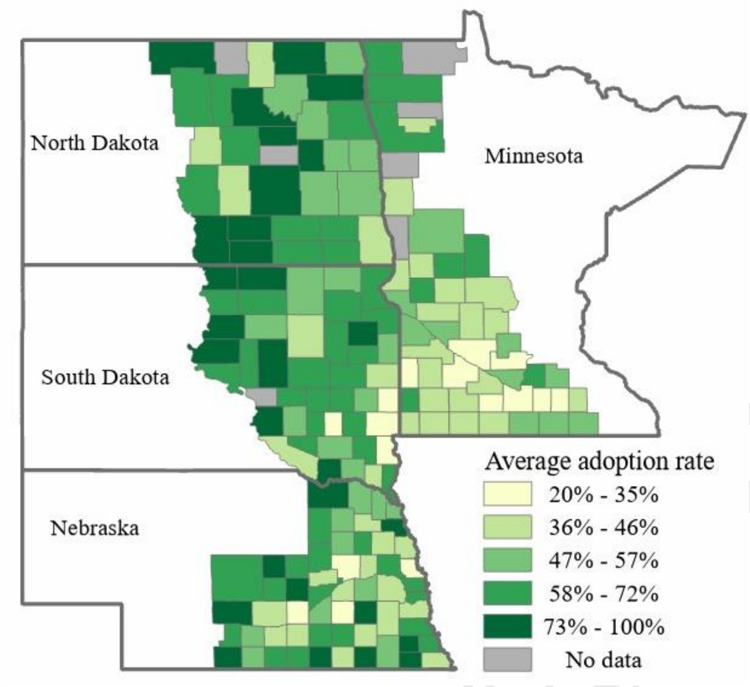

Figure 1. Survey states and average EAPs adoption rate in a county Theoretical Model

$$C = \theta(c, e, w) + K(x) \tag{2}$$

Where $\theta(c, e, w)$ represents the variable cost (e.g., labor) and $K(x)$ is the fixed cost (machinery, learning cost, etc.).

Farmers optimize input amounts under different categories to maximize profits (π) that is shown in equation (3):

$$\pi = p.f(c, e, w) - C \tag{3}$$

Where p is the price per unit of crop yield. The environmental outcome is comprised of negative externality (ξ_n) (e.g., nutrient runoff, greenhouse gas emissions) from the conventional system (4) and positive externality (ξ_p) (e.g., improved soil health, biodiversity) from the ecological system (5), together add up to the overall environmental impact (ξ).

$$\xi_n = g_c(c, w) \tag{4}$$

$$\xi_p = g_e(e, w) \tag{5}$$

$$\xi = \xi_n + \xi_p \tag{6}$$

Farmers' decision-making is inherently complex and polychotomous, driven by multiple objectives. Drawing on the multi-utility framework by Chouinard et al. (2008) and Lynne (1999), farmers can be broadly categorized into three types based on their primary motive: profit-maximizers, non-profit interest farmers, and mixed-motive farmers. For pure profit-maximizers, as defined by the indifference function in equation (7), the farmer seeks to maximize utility at the point where the indifference curve is tangent to the production possibilities frontier (Figure 2). At this point, the farmer generates the associated profit and environmental effects.

$$I_1 = I_1(\pi) \tag{7}$$

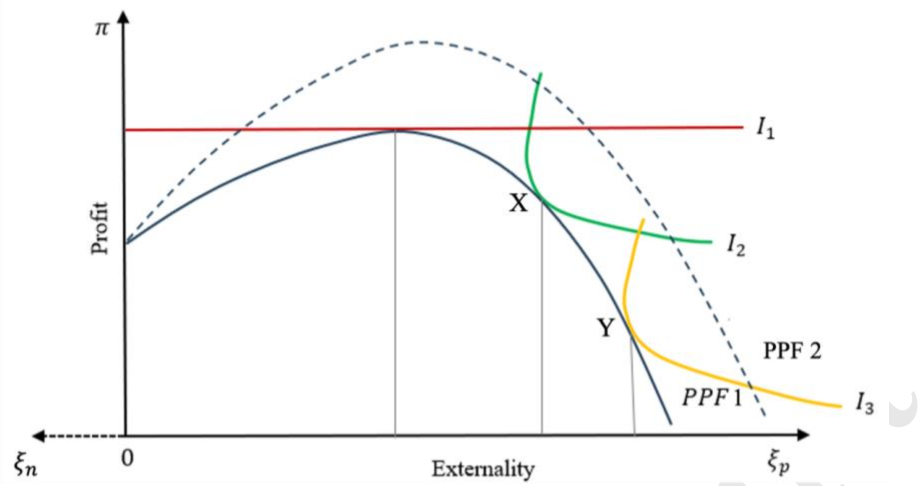

Figure 2. Production possibilities frontier showing trade-offs between net profit and externality

Figure 2 illustrates the trade-off between farm-level net profit and environmental externalities using a production possibilities frontier (PPF). The solid curve represents the baseline PPF under the existing production technologies. The indifference curve for profit-maximizers (I_1), is a straight line since the farmer is indifferent to environmental externalities. The farmer maximizes utility at the point of tangency between I_1 and PPF 1. To the left of the maximum point of PPF 1, increases in net environmental impacts are consistent with an increase in profits. To the right of the maximum point of PPF 1, however, an increase in positive externality is associated with a decrease in profits. This occurs because generating further environmental benefits necessitates reallocating resources from profit-maximizing production activities.

The dashed curve, PPF 2, depicts an outward-shift in the frontier when conservation policy incentives are applied. For a given level of externality, PPF 2 produces a higher profit level with lower externality than PPF 1. The PPF 2 shows the frontier where policies such as EQIP/CSP, cost-share, carbon credit, technical assistance, and incentive environmental performance. The incentives enter profits as:

$$\pi' = p.f(c,e,w) - \theta(c,e,w) - K(x) + s(x) + \tau\xi_p \tag{8}$$

Where $s(x)$ is the cost-share and $\tau\xi_p$ represents the monetized environmental output (e.g., carbon).

Now, we consider the case (I_2) where a farmer adopts practices based on private amenity utility (self-interest), to generate profit and environmental amenities for her personal purposes such as hunting, hiking, or other benefits. The indifference function for such a farmer is specified as:

$$I_2 = I_2(\pi, \xi) \tag{9}$$

The indifference curve (I_3) in (10) represents the utility a farmer gains from adoption practices based on social interest (pure social utility) or because it is considered a good thing for society.

$$I_3 = I_3(\pi, \xi) \tag{10}$$

The farmer motivated either by self-interest (I_2) or by social interests typically (I_3) opt to produce at points of X and Y as shown in the PPF. Our empirical analysis tests whether profit-oriented and stewardship-oriented motives jointly influence adoption of practices associated with both economic and ecological benefits.

Empirical Models

The individual decision maker (farmer) will choose the option that generates the greatest expected utility (Greene, 2018). The adoption decision is dichotomous, where $Y_i = 1$ denotes adoption of EAP, and $Y_i = 0$ represents non-adoption. The condition for adoption is expressed as:

$$(11) \qquad Y_i = \begin{cases} 1, if\ E(U_{1)} \geq E(U_0) \\ 0, if\ otherwise \end{cases}$$

Where $E(U_1)$ and $E(U_0)$ represent the expected utility of adoption and non-adoption respectively. Based on expected utility theory, a farmer tends to adopt a bundle of practices that maximize expected utility. For profit-maximizers, the net profit from adoption is specified as:

$$(12) \qquad \Delta\pi = {\pi_i}^1 - {\pi_i}^0$$

Based on equation (11), adoption occurs if the expected utility from adoption outweighs the utility from non-adoption, which is specified as:

$$(13) \qquad E[U(1, {\pi_i}^1, X)] > E[U(0, {\pi_i}^0, X)]$$

Where ${\pi_i}^1$ denotes the profit from adoption, ${\pi_i}^0$ represents the profit from non-adoption, and X denotes a vector of observed covariates that influence profitability. For environmental stewards, adoption occurs at a point where adoption leads to better social environmental gain:

$$(14) \qquad E\left[U(1, {S_i}^1, X)\right] > E\left[U(0, {S_i}^0, X)\right]$$

Where ${S_i}^1$ and ${S_i}^0$ are the stewardship utilities farmers derived from adoption and non-adoption of the practice, respectively. Ecological practices produce joint products of private goods (yield stability, reduced input costs) and public goods (water filtration, habitat provision). The overall utility is specified as:

$$(15) \qquad U = E[U({\pi_i}^a) + \gamma {S_i}^a] \quad (a = 0\ or\ 1)$$

Where γ is the relative weight farmers place on the environmental stewardship satisfaction, ${S_i}^a$ $(a = 0\ or\ 1)$. Farmers with strong stewardship ethics (higher γ) are more likely to adopt EAPs, yet those placing lower weight behave more like standard profit-maximizing agents.

Our study considers five ecological agriculture practices (CT, CC, DCR, ICLS, and FE). As such, we adopt a multivariate form of the binary probit model, specified as:

$$(16) \qquad {Y_{ik}}^* = \beta_k' X_{ik} + \alpha P_i + \gamma S_{ik} + \varepsilon_{ik}$$

Where k = CT, CC, DCR, ICLS, and FE, with error terms distributed as multivariate normal, P_i denotes the profit interest for farmer i and S_{ik} is the stewardship interest for farmer i using the kth practice ${Y_{ik}}^*$ denotes the latent variable and X_{ik} signifies a vector of other explanatory variables, $\beta_k^{'}$ are the coefficients to be estimated for practice k, and ε_{ik} are the error terms.

In addition, the MVP model allows for the complementarity or substitutability of the practices based on the correlation coefficients (ρ_{kj}) from $Cov(\varepsilon_{ik}, \varepsilon_{ij})$ (e.g., Belderbos et al., 2004). When $\rho_{kj} > 0$, the practices are complements while $\rho_{kj} < 0$ indicates that the practices are substitutes.

The data for this study are derived from a cross-sectional survey, which raises potential concerns regarding endogeneity. To mitigate this issue, a comprehensive set of controls were included, encompassing farm and farmer characteristics, farmer perception factors, and soil and climate variables, to account for observable sources of heterogeneity. State fixed effects were also incorporated to control time-invariant differences across states. However, we acknowledge that this strategy does not fully resolve the endogeneity issue. Section 5.3 discusses this limitation and its implications for interpreting the results.

A count dependent variable, the number of EAPs adopted by farmers (ranging from 0 to 5), was used to measure adoption intensity. Count data regression approaches have been used previously to model the intensity of agricultural practices and technologies (e.g., Cameron and Trivedi, 2013; Greene, 2018; Ehiakpor, Danso-Abbeam, and Mubashiru, 2021; Kolady et al., 2021).

In the count model analysis, the dependent variable is assumed to be a non-negative integer with a small mean and variance, and follows a Poisson distribution with equal mean and variance (Greene, 2018).[1] In our sample, the dependent variable (adoption intensity) has an unconditional mean of approximately 2.6 and a variance of about 2.2, indicating no significant overdispersion or under dispersion and that the Poisson model can be used for estimation.[2] Therefore, this study uses the standard Poisson regression as the count model to assess the factors influencing the adoption intensity of EAPs. The adoption intensity model is specified as:

$$Y_i = \beta_0 + \beta_1 \pi_{ik} + \beta_2 S_{ik} + X_{ik} + \varepsilon_i \tag{17}$$

Where Y_i is the count dependent variable, π_{ik} represents farmer i's expected economic return from adopting practice, S_{ik} is the non-pecuniary satisfaction or stewardship utility associated with practice k, and the other variables not explained are the same as previously elaborated. Like the MVP model, equation (17) is also estimated using the maximum likelihood estimation. As a result, the marginal effects for Poisson models must be computed to ensure meaningful interpretation of the estimated relationships.

Results and Discussion

Table 4 presents the estimated coefficients for the determinants of the EAPs from the MVP regression. The results from models 1–5 show that, except for conservation tillage, ecological credit has a positive and significant effect at the 5% level or better on the adoption of EAPs. This means that a unit increase in farmers' perception of ecological credit makes farmers more likely to adopt most EAPs. Conversely, profit-maximization is inversely related to CC, ICLS, and FE at 5% significance level. These findings are consistent with Chouinard et al. (2008) and Wang et al. (2019), who show that both stewardship and financial motives determine farmers' adoption decisions.

Complementarity of Ecological Agriculture Practices

We can use the results from MVP regressions to estimate the level of complementarity for the EAPs, as shown in Table 5. The results show that all ecological practices are complementary, suggesting that a farmer adopting an EAP is more likely to adopt another, possibly due to the synergies among practices. However, the level of complementarity differs in significance and magnitude.

DCR and ICLS are the most complementary practices, with a positive correlation of 0.50. This correlation indicates that farmers who adopt DCR are significantly more likely to adopt ICLS. ICLS often require adjustment to rotation structure to accommodate forage and grazing needs, making DCR a natural precursor to integrated systems (Russelle, Entz, and Franzluebbers, 2007; Roesch-McNally, Arbuckle, and Tyndall, 2018a; Wang et al., 2019). This advantage is partly due to the interdependent benefits of extended rotations and livestock grazing, which allow livestock manure to be applied to fields to reduce fertilizer costs and produce livestock feed from crop production. Farmers who adopt ICLS are also more likely to adopt FE, while CC adopters

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[1] Due to the complexity of evaluating multivariate normal integrals, simulation-based methods like the GHK simulator or simulated likelihood are used to estimate large models efficiently (Greene, 2018).

[2] When the conditional mean approaches the conditional variance, it is referred to as equi-dispersion. However, when the conditional variance exceeds the conditional mean, it is referred to as over-dispersion, and vice versa for under-dispersion.

Table 4. Adoption determinants for practices from the multivariate probit regression

	CT (1)	CC (2)	DCR (3)	ICLS (4)	FE (5)
Age	-0.004	-0.006	-0.003	-0.006	-0.001
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
ln(miles)	0.059	0.033	0.038	0.071*	-0.056
	(0.058)	(0.045)	(0.048)	(0.042)	(0.044)
ln(cropland acres)	0.171**	0.124**	0.075	-0.031	0.076
	(0.077)	(0.060)	(0.051)	(0.061)	(0.050)
Acres owned	0.236	-0.148	0.147	0.481***	0.075
	(0.181)	(0.147)	(0.160)	(0.160)	(0.139)
Education	0.168***	0.153***	-0.004	0.042	0.099*
	(0.060)	(0.048)	(0.055)	(0.055)	(0.053)
Off-farm income	0.033	0.037	0.058*	-0.022	0.028
	(0.040)	(0.033)	(0.032)	(0.031)	(0.031)
Weather resilience	0.405***	0.189***	0.125**	0.055	0.015
	(0.068)	(0.067)	(0.053)	(0.058)	(0.054)
Ecological credit	0.007	0.154**	0.202***	0.156***	0.136**
	(0.062)	(0.065)	(0.062)	(0.058)	(0.055)
Weather frequency	-0.009	0.079*	-0.076	-0.012	-0.014
	(0.048)	(0.043)	(0.047)	(0.041)	(0.041)
Profit-maximization	-0.072	-0.116**	-0.003	-0.087**	-0.083**
	(0.059)	(0.049)	(0.046)	(0.041)	(0.042)
LCC	-0.819***	-0.287	-0.371**	-0.089	-0.278
	(0.264)	(0.203)	(0.179)	(0.186)	(0.174)
Precipitation	0.001	-0.003***	-0.008***	-0.003**	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature	0.154*	0.020	0.058	0.006	0.066
	(0.087)	(0.068)	(0.078)	(0.071)	(0.070)
Constant	0.858***	0.643***	0.223	-0.193	-0.864***
	(0.275)	(0.232)	(0.213)	(0.270)	(0.192)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	963	963	963	963	963

Joint log pseudolikelihood = -2639.375
Likelihood ratio test chi-square = 285.206

Notes: The multivariate probit model estimates are obtained using 100 simulation draws. The standard errors in parentheses are clustered at the county level. Significance levels of *** p<0.01, ** p<0.05, * p<0.1

are also more likely to adopt DCR. Incorporating CC into annual crop rotations enhances the ecosystem services provided by agricultural systems by diversifying the crop varieties (Schipanski et al., 2014).

We found a moderate complementarity between CC and ICLS (0.32), CT and CC (0.33), and DCR and FE (0.30). This positive correlation indicates that farmers who adopt CC are more likely to adopt ICLS and CT. Previous studies have found a complementary relationship between cover crops and no-till practice (Canales, Bergtold, and Williams, 2020; Gong, Bergtold, and Yeager, 2021). This is consistent with the findings of Singh et al. (2021), which show that incorporating CC with no-till in corn-soybean rotation provides an economically feasible solution while

Table 5. Correlation coefficients indicating complementarity from the multivariate probit model

Practices	Estimate
CT & CC	0.327***
	(0.060)
CT & DCR	0.136**
	(0.067)
CT & ICLS	0.108*
	(0.058)
CT & FE	0.216***
	(0.063)
CC & DCR	0.425***
	(0.048)
CC & ICLS	0.324***
	(0.052)
CC & FE	0.126***
	(0.048)
DCR & ICLS	0.495***
	(0.044)
DCR & FE	0.296***
	(0.054)
ICLS & FE	0.458***
	(0.042)
Likelihood ratio test chi-square	285.206
Observations	963

Notes: Significance levels of *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

diversifying the cropping system. In contrast, the coefficients of FE and CC (0.13) and CT and ICLS (0.11) indicate a weak complementarity between the pairs of practices, which could be attributed to differences in their spatial and operational focus. FE practices typically result in off-site environmental benefits, whereas CC provides both in-field improvements and off-site benefits (Wang et al., 2021a). Also, the limited complementarity between CT and ICLS could be attributed to the complexity and operational hurdles that farmers face to adopt them (Russelle, Entz, and Franzluebbers, 2007).

Adoption Intensity of Ecological Agriculture Practices

Table 6 reports the estimated marginal effects on EAPs adoption intensity. The result in model 1 serves as the baseline specification, while model 3 extends it by incorporating soil and historical climatic variables. Models 2 and 4 build upon models 1 and 3, respectively, by including state dummies to account for state-level variation in the sample. This allows us to assess how controlling state heterogeneity influences the estimated coefficients. We focus our interpretation on model 4, which captures all covariates and thus provides the most comprehensive specification**.** Results from models 1–3 show that our results are robust.

Table 6. Marginal effects on adoption intensity: Poisson regression findings

	Model 1	Model 2	Model 3	Model 4
Age	-0.008**	-0.008**	-0.007**	-0.007**
	(0.004)	(0.003)	(0.003)	(0.004)
ln(miles)	0.040	0.032	0.045	0.042
	(0.045)	(0.044)	(0.044)	(0.044)
ln(cropland acres)	0.280***	0.157***	0.110**	0.107**
	(0.052)	(0.055)	(0.053)	(0.054)
Acres owned	0.415***	0.336**	0.273*	0.263*
	(0.154)	(0.154)	(0.149)	(0.152)
Education	0.155***	0.138***	0.144***	0.145***
	(0.054)	(0.052)	(0.050)	(0.050)
Off-farm income	0.017	0.022	0.036	0.035
	(0.031)	(0.031)	(0.030)	(0.030)
Weather resilience	0.303***	0.248***	0.234***	0.231***
	(0.061)	(0.059)	(0.057)	(0.057)
Ecological credit	0.249***	0.247***	0.223***	0.227***
	(0.058)	(0.056)	(0.054)	(0.054)
Weather frequency	-0.031	-0.018	0.005	0.002
	(0.044)	(0.043)	(0.042)	(0.043)
Profit-maximization	-0.122***	-0.120***	-0.109***	-0.109***
	(0.044)	(0.042)	(0.042)	(0.042)
LCC			-0.434***	-0.415***
			(0.141)	(0.153)
Precipitation			-0.007***	-0.005***
			(0.001)	(0.001)
Temperature			0.082***	0.060
			(0.029)	(0.059)
ND		0.840***		0.229
		(0.127)		(0.187)
NE		0.536***		0.156
		(0.116)		(0.220)
SD		0.771***		0.299*
		(0.120)		(0.163)
Log pseudolikelihood	-1735.17	-1715.40	-1706.70	-1705.55
Corrected AIC	3492.62	3459.23	3441.83	3445.73
BIC	3546.25	3527.40	3509.98	3528.38
Observations	992	992	991	991

Notes: Standard errors in parentheses are clustered at the county level. Significance levels of *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Across all four models, age is negatively associated with adoption intensity at 5% significance level, which is consistent with prior findings that older farmers tend to adopt fewer conservation or ecological practices due to shorter planning horizons and greater risk aversion (Ervin and Ervin, 1982; Baumgart-Getz, Prokopy, and Flores 2012; Prokopy et al., 2019). Our finding also indicates that cropland acres, expressed in natural logarithmic form, has a positive and statistically significant effect on adoption intensity, with a 10% increase in cropland acres increasing adoption intensity by 0.011 units. This could be explained by the effect of economies of scale, as large-scale farms are able to spread the fixed costs over a larger land base (Soule, Tegene and Wiebe, 2000). The proportion of land owned also had a significant and positive effect on adoption intensity. This shows that secure land tenure provides farmers with more incentives to invest in ecological practices that require multi-year commitments (e.g., Soule, Tegene, and Wiebe 2000).

Education shows a positive, statistically significant effect (at 1% level) on adoption intensity across all models. A one-level increase in the farmer's educational level is associated with a 0.15 increase in adoption intensity. This result is consistent with the view that education enhances farmers' access to information, analytical capacity, and awareness of the long-term benefits of conservation-oriented practices. These farmers are also better positioned to understand and utilize new machinery for these practices (Knowler and Bradshaw, 2007; Genius et al., 2006).

The perception that EAP will improve weather resilience has a positive and statistically significant role with adoption intensity across all models at 1% significance level. A one-unit increase in perceived resilience increases adoption intensity by 0.23 units. This suggests that farmers who view ecological practices as adaptive mechanisms are more likely to incorporate them into their management portfolios. The result is congruent with prior findings that risk-mitigation and resilience-oriented perceptions drive the adoption of climate-adaptive practices (Arbuckle, Morton, and Hobbs 2013; Prokopy et al., 2019).

The results reveal that both ecological credit and profit-maximization play significant roles in adoption intensity. A one-unit increase in ecological credit motivation increases the adoption intensity of EAP adoption by 0.23 units. This reinforces evidence that stewardship motives are a key driver of conservation behavior (Reimer, Thompson, and Prokopy, 2012; Roesch-McNally, Arbuckle, and Tyndall, 2018b; Prokopy et al., 2019).

In contrast, profit-maximization motive has a negative and statistically significant effect on adoption intensity, with a one-unit increase reducing intensity by approximately 0.11 units. This finding is emphasized by prior literature, including Chouinard et al. (2008), Wang et al. (2019), and Thompson, Barnes, and Toma (2022), which reveal that farmers who emphasize short-term profit are less likely to adopt practices that improve long-term soil and environmental benefits. To determine if cost considerations drive this relationship, we classified the five practices as two groups: cost-intensive (CC and FE) and cost-saving (DCR, ICLS, and CT) following Wang et al. (2019) and Wang et al. (2021a). Poisson regression results for each of the two groups indicate that profit-maximization has a stronger negative effect on adoption intensity of cost-intensive practices. Specifically, profit-maximization decreases adoption intensity by 0.24 for cost-intensive practices, compared with 0.11 for cost-saving practices (Table A1 in the appendix).

The land capability class (LCC) variable shows a negative and statistically significant effect on adoption intensity at 1% level in models 3 and 4. The marginal effects indicate that farmers with a higher proportion of Class I and II soils, which are considered the most productive, are less likely to intensify the adoption. This finding is plausible and consistent with the perspective that farmers operating on lower-quality or more erosion-prone soils have stronger incentives to invest in conservation-oriented or ecological practices to enhance productivity and control environmental risks (Prokopy et al., 2008; Csikós and Tóth, 2023).

The results also show that precipitation has a significant and negative effect. As average precipitation increases by 10 mm, the adoption intensity decreases by 0.05. This aligns with the adoption literature, which shows that farmers in drought-prone regions are more likely to adopt water-conserving practices such as diversified crop rotation, no-till, and reduced tillage (Wang et al., 2021b; Etumnu et al., 2023).

Potential Endogeneity Issues

While the model specification accounts for a wide range of controls as well as state fixed effects, several latent drivers of EAPs adoption behavior remain difficult to capture in cross-sectional survey data. First, omitted variables such as production risk and risk perceptions, innovativeness, and liquidity/credit constraints, have been shown to influence both environmental attitudes and adoption decisions (Pannell et al., 2006, Prokopy et al., 2019 Campbell et al., 2021; Turner et al., 2025). Second, unobserved heterogeneity, including managerial ability, intrinsic stewardship preferences, and farm-specific opportunity costs may jointly determine EAPs adoption motivations and participation outcomes, resulting in self-selection effects (Baumgart-Getz et al., 2012; Michler et al., 2019; Schaub et al., 2023). Third, reverse causality may occur because adoption itself can influence reported motivations through learning-by-doing or cognitive effect, unobserved shocks, suggesting that ecological attitudes may partially reflect post-adoption experiences (Michler et al., 2019; Zhong and Hu, 2019).[3] While a few previous studies on conservation adoption addressed endogeneity using instrumental variables (e.g., Federal Crop Insurance Program (FCIP) premium rating) and the control function approach (e.g., Yu, Smith, and Sumner, 2018; Turner et al., 2025), potential endogeneity remains an issue in the context of this study due to the lack of valid instrumental variable (IV). Therefore, the results are best interpreted as a well-defined association rather than definitive causal inference.

In our modeling context, it is important to recognize that unobserved farmer-specific characteristics that determine farmer adoption decisions could also affect estimates of ecological-credit perceptions and profit-maximization. For instance, unobserved factors like stewardship identity, or social norms that support conservation, can increase both ecological-credit responses and the likelihood of adoption. This may lead to higher ecological-credit coefficients than expected (upward bias). Conversely, unobserved financial constraints, production risk, and risk preferences can reinforce a profit-maximization orientation while discouraging the adoption of practices with delayed benefits, which may result in more negative profit-maximization estimates (downward bias). In addition, latent factors such as stewardship identity and managerial innovativeness can increase the likelihood of simultaneous adoption of multiple practices. Without accounting for these common drivers, the residual correlation across adoption equations in the multivariate probit model may capture shared unobserved influences, potentially affecting the estimated degree of complementarity among EAPs.

Conclusion and Policy Implications

This study uses survey-based data collected from four Midwestern states with a focus on a variety of ecological agriculture practices (EAPs), notably cover crops (CC), conservation tillage (CT), diversified crop rotation (DCR), integrated crop-livestock systems (ICLS), and field edge (FE), to provide empirical evidence on the complementarity of the ecological agriculture practices (EAPs) and the motivations behind farmers' decisions to intensify adoption of these practices.

The MVP estimates show that all the EAPs exhibit varying degrees of complementarity. We found that DCR and ICLS are the most complementary practices (50%), while CT and ICLS are the least complementary practices (11%). The results from the Poisson regression models, which show intensity of adoption, indicate that both ecological and economic motivations significantly influence EAPs' adoption intensity. While the longer-term ecological benefits increase EAPs adoption intensity, farmers who prioritize profit-maximization are less likely to increase EAP adoption intensity. In addition, factors such as younger age, higher education levels, larger cropland, lower precipitation levels, and stronger agreement with the weather resilience feature of EAPs contribute to increased adoption intensity. Given the cross-sectional nature of the data, unobserved farmer-specific factors may influence both reported motivation and the adoption of practices. Therefore, the results should be regarded as indicative of behavioral relationships rather than definitive evidence of causal effects.

Our findings offer several important implications for promoting more intensive adoption of EAP practices. The observed complementarity between practices supports the use of bundle-based

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[3] For example, it is plausible that EAPs influence key variables such as profit-maximization and ecological credit. Conversely, these variables may also affect the adoption of EAPs.

policy instruments. Instead of incentivizing practices individually, policymakers may achieve greater adoption at lower cost by targeting one practice as a catalyst for the adoption of other strongly complementary practices. For instance, incentivizing diversified crop rotations may naturally lead to the subsequent adoption of integrated crop–livestock systems. This strategy improves cost-effectiveness and enhances ecological outcomes across the system.

The findings suggest that conservation efforts are more effective when employing a two-pronged approach to encourage intensive adoption. Relying exclusively on short-term financial incentives is insufficient. Highlighting environmental co-benefits is particularly effective for pro-environmental and younger farmers. Furthermore, mechanisms such as cost-sharing, performance-based payments, and transition support can address the gap between initial costs and delayed ecological benefits. Carefully structured incentives may lower financial barriers for profit-oriented farmers who might otherwise delay adoption.

A limitation of this study is its reliance on cross-sectional data, which prevents analysis of adoption sequencing and dynamic adjustments over time. Future research could utilize panel data to investigate the adoption paths of complementary conservation practices, such as the progression from early adoptions toward comprehensive ecological practice portfolios, and the effects of economic shocks or policy changes on adoption intensity trajectories. Finally, data limitations and lack of valid instruments prevent us from fully addressing potential endogeneity concerns. Future studies could strengthen causal inference by exploiting appropriate instrumental variable approaches in survey design to better account for potential endogeneity.

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Appendix

Table A1. Marginal effects on adoption intensity by cost-intensive and cost-saving practices

	Cost intensive (1)	**Cost saving (2)**
Age	-0.009	-0.000
	(0.006)	(0.006)
ln(miles)	-0.000	0.226***
	(0.074)	(0.087)
ln(cropland acres)	0.232**	0.144
	(0.093)	(0.099)
Acres owned	0.064	0.121
	(0.261)	(0.316)
Education	0.235***	0.145*
	(0.082)	(0.087)
Off-farm income	0.061	0.034
	(0.053)	(0.049)
Weather resilience	0.374***	0.372***
	(0.115)	(0.119)
Ecological credit	0.285***	0.239**
	(0.093)	(0.100)
Weather frequency	0.053	-0.013
	(0.072)	(0.079)
Profit-maximization	-0.236***	-0.105
	(0.063)	(0.070)
LCC	-0.485**	-0.435
	(0.235)	(0.271)
Precipitation	-0.008***	-0.003
	(0.002)	(0.003)
Temperature	0.075	0.039
	(0.101)	(0.108)
State FE	Yes	Yes
Observations	500	368

Notes: Model 1 includes the cost-intensive practices (CC and FE) while model 2 focuses on all three cost-saving practices (DCR, ICLS, and CT). The categorization of the practices follows Wang et al. (2019) and Wang et al. (2021). Standard errors in parentheses are clustered at the county level. Significance levels of *** p<0.01, ** p<0.05, * p<0.1.