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Does the Adoption of Green Pest Control Technologies Help Improve Agricultural Efficiency?

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Abstract

The adoption of green pest control technologies (GPCTs) has emerged as a critical factor in the pursuit of sustainable agricultural practices, particularly in improving farm efficiency and mitigating environmental impacts. This study investigates the effect of GPCT adoption on the technical efficiency of apple farmers in Shandong Province, China, using survey data collected in 2022. Applying advanced econometric techniques, including stochastic frontier analysis (SFA) to measure technical efficiency and endogenous switching regression model (ESR) to address endogeneity and selection bias, the findings indicate that GPCT adoption significantly enhances farmers' technical efficiency. Specifically, under the counterfactual scenario of adoption, non-adopters' technical efficiency would increase by 18.2% (from 0.669 to 0.851), whereas adopters would experience a 3.9% efficiency gain attributable to adoption (from the counterfactual 0.700 to the observed 0.739). The analysis further reveals that lower-income farmers benefit disproportionately from GPCT adoption, suggesting that the technology offers greater potential to enhance the productivity of resource-constrained farmers. These results underscore the importance of targeted policy interventions, such as subsidies and agricultural extension programs, to foster the widespread adoption of GPCTs, particularly among lower-income groups. This study contributes to the literature by providing empirical evidence of the dual benefits of GPCT adoption: improving farm efficiency while promoting environmental sustainability, with important implications for policy formulation in developing economies.

Keywords: pest control; green pest control technologies; technical efficiency; sustainable agriculture; endogenous switching regression model (ESR)

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1. Introduction

Improving total factor productivity (TFP)—commonly defined as the efficiency with which all production inputs (e.g., labor, land, and capital) are jointly transformed into agricultural output—is widely recognized as a central pathway toward sustainable agricultural development, especially as contemporary agricultural systems confront mounting natural and socio-economic constraints [1]. These constraints include a rising food demand driven by population growth, increasing climatic risks, shrinking arable land, and an aging rural labor force [2]. Under such pressures, enhancing the efficiency with which farmers allocate labor, land, and capital has become essential for sustaining agricultural output and rural livelihoods.

In apple production, efficiency improvement is particularly urgent. Apple farming has long relied on high-intensity chemical inputs, especially pesticides and fertilizers,

to stabilize yields and control pests [3,4]. Although this strategy has supported production in the short run, it has also generated growing challenges, including higher production costs, pesticide residue risks, and ecological externalities such as soil and water contamination [3,5,6]. These concerns have stimulated demand for more environmentally sound pest-management approaches that can maintain yield stability while reducing the dependence on chemical pesticides [7].

In this study, green pest control technologies (GPCTs) refer to a suite of environment-friendly pest-management techniques, including ecological regulation, biological control (e.g., biopesticides and the use of natural enemies), physico-chemical inducement/trapping (e.g., insecticidal lamps and color/pheromone traps), and scientific pesticide-use technologies (i.e., judicious and targeted pesticide application when necessary) [8]. Importantly, these components may differ in cost, complexity, and effectiveness; our empirical analysis does not impose that each component contributes equally. Instead, we estimate the average efficiency effect of any GPCT adoption relative to non-adoption, which is policy-relevant given that local extension programs typically promote these practices as a package. In addition, Integrated pest management (IPM) is an ecosystem-based pest-management strategy that integrates multiple tactics (biological, cultural, physical, and chemical measures) based on monitoring and decision-making rules, rather than a single control method; in China, green control technologies are widely promoted and implemented as important practices aligned with the IPM framework [9]. By replacing or reducing chemical pesticide use and improving the precision and effectiveness of pest and disease management, GPCTs may raise output quality, lower control costs, and strengthen ecological sustainability [10]. From an economic perspective, these technologies are expected to impact agricultural performance not only through yield or income effects but also through changes in the efficiency of input use, thereby potentially improving farmers' technical efficiency [11].

Internationally, the promotion of green agricultural technologies has been accelerated, supported by policy instruments such as the EU's agri-environmental schemes and U.S. environmental incentive programs [12]. However, in many developing regions, adoption remains constrained by limited access to information, capital, and technical services [13,14]. As the world's largest apple producer, China has placed GPCT promotion at the core of its green agricultural transformation. Policies emphasizing pesticide reduction and ecological production are being implemented nationwide [15], but empirical evidence on whether GPCT adoption improves farmers' technical efficiency—and for whom such benefits are the most significant—remains limited [16].

Existing research on green agricultural technologies has primarily focused on adoption determinants and their impacts on yields or household income [17]. However, relatively little attention has been paid to how GPCT adoption affects farmers' technical efficiency, a crucial component of TFP and long-term sustainability [18]. Moreover, because adoption decisions are endogenous and potentially subject to both observable and unobservable selection, conventional estimation strategies may lead to biased conclusions [19]. In addition, farmers' resource endowments (e.g., income levels) may shape both adoption capacity and efficiency gains, implying heterogeneous effects that have not been sufficiently explored [20]. From a sustainability and productivity perspective, however, focusing solely on yield or income may overlook whether green pest-control transitions improve the efficiency of input use, which ultimately underpins TFP growth.

To address these gaps, this study investigates the impact of GPCT adoption on the technical efficiency of apple farmers in Shandong Province, China. Using micro-survey data collected in 2022 from major apple-producing counties in Yantai and Linyi, we first estimate farmers' technical efficiency through a stochastic frontier analysis method (SFA) framework [21]. We then employ an endogenous switching regression model (ESR) to

correct for endogeneity and self-selection in adoption, enabling a credible estimation of the causal efficiency effect of GPCT adoption [19]. Furthermore, we examine heterogeneity across income groups to identify whether GPCTs generate larger efficiency gains for resource-constrained farmers.

This study contributes to the literature in three ways. While existing studies on IPM/green pest-control adoption in China have largely focused on adoption determinants and outcome indicators such as pesticide reduction, yields, or household income, our study advances the evidence base in both conceptual and methodological terms. First, we shift the evaluation focus to technical efficiency, a core component of TFP and a key metric for long-run sustainable intensification, thereby assessing whether GPCT adoption improves the efficiency with which multiple inputs are converted into output rather than only changing output or income levels. Second, by integrating SFA for efficiency measurement with an ESR model framework, we correct for both observable and unobservable selection in adoption decisions and provide more credible estimates of the causal efficiency effect. Third, we document income-based heterogeneity in efficiency gains, highlighting distributional implications of GPCT diffusion and informing more targeted and inclusive policy design.

2. Mechanism Underlying the Impact of Green Pest Control Technology Adoption on Farmers' Technical Efficiency

GPCTs play a crucial role in enhancing farmers' technical efficiency by optimizing pest and disease management [11,22]. These technologies are designed to increase the efficiency of pest control, reduce pesticide input costs, and improve output quality, thus contributing to higher agricultural productivity [23–25]. As shown in Figure 1, the mechanisms through which GPCTs enhance technical efficiency can be broadly categorized into two pathways: factor substitution and factor optimization.

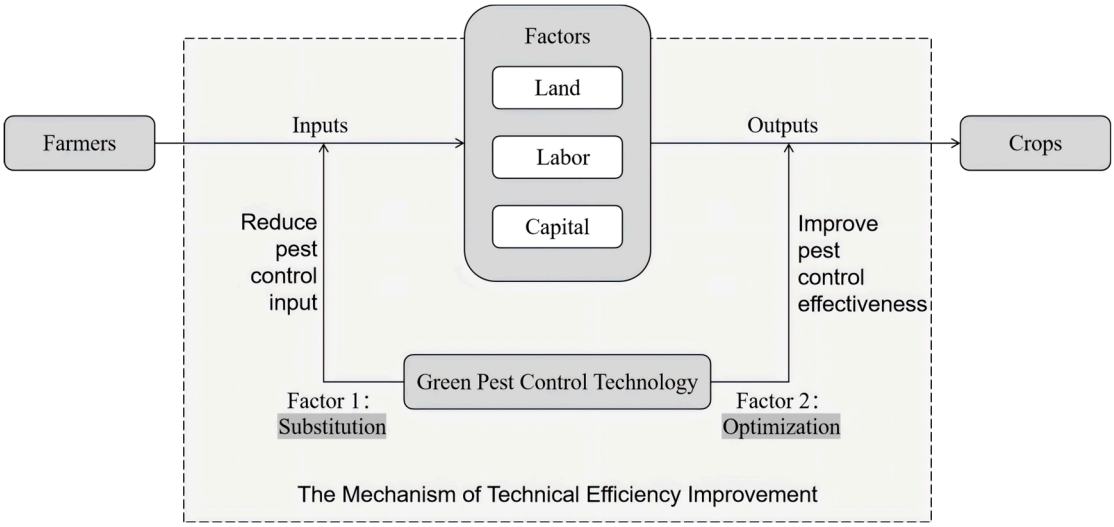

Figure 1. Pathway diagram showing impact of green pest control technology on farmers' technical efficiency.

Figure 1 Pathway diagram illustrating how GPCT adoption may enhance farmers' technical efficiency through factor substitution and factor optimization. The figure provides a conceptual interpretation framework; empirically, technical efficiency is first estimated using an SFA model, and the overall effect of GPCT adoption is identified using an ESR model, without decomposing impacts by individual channels.

2.1. Mechanism of Factor 1: Substitution

One of the primary mechanisms through which GPCTs improve technical efficiency is the substitution of chemical pesticides with more cost-effective and environmentally friendly alternatives [23,26]. By adopting biopesticides or IPM techniques, farmers can reduce their dependency on chemical inputs, which are often expensive and can lead to diminishing returns over time [23]. Studies have shown that substituting chemical pesticides with green alternatives reduces input costs, lowers pesticide overuse, and enhances overall farm efficiency [27]. For apple farmers, this reduction in pesticide use not only reduces costs but also environmental harm, improving the long-term sustainability of their operations [4,5].

2.2. Mechanism of Factor 2: Optimization

The second pathway through which GPCTs enhance efficiency is through factor optimization. GPCTs optimize the use of available resources, particularly labor and capital, by improving pest control efficacy and reducing the need for repeated pesticide applications [28]. For example, biopesticides and IPM methods have been found to offer more targeted, effective pest control, which in turn enhances both the quantity and quality of apple production [29]. This optimization leads to higher output per unit of input, increasing per-acre apple income and boosting technical efficiency.

Together, these two mechanisms—substitution and optimization—demonstrate how GPCT adoption can increase farmers' technical efficiency, not only by reducing costs but also by improving the quality of inputs and outputs. Previous studies have indicated that green production technologies lead to higher technical efficiency by enhancing resource allocation [30,31], but the specific effects of GPCT adoption on apple farming efficiency require further empirical examination.

2.3. Hypothesis

Based on the above mechanisms, we postulate the following hypothesis:

H1: *The adoption of green pest control technologies significantly improves the technical efficiency of apple farmers.*

3. Model Construction and Variable Selection

3.1. Model Construction

3.1.1. Estimating Farmers' Technical Efficiency: Stochastic Frontier Analysis Method

There are various methods of measuring agricultural production efficiency, mainly including single-factor and total factor productivity [32]. Single-factor productivity refers to the ratio of output level to the input quantity of a particular production factor [33], and common types include labor and land productivity. This approach assumes that farmers are operating in an optimal factor market, where there are no efficiency losses during production. In contrast, total factor productivity refers to the total efficiency level at which inputs are converted into outputs during agricultural production, excluding the impact of other factors on output [32,33]. Among these, farmers' technical efficiency is an essential component of total factor productivity. It measures the efficiency of resource allocation from the perspective of input–output, reflecting the ratio of actual output to optimal output when the production method and input factors remain unchanged. This measurement incorporates the existence of efficiency losses in agricultural production, thus better reflecting the actual agricultural production of farmers. On this basis, this study selects farmers' technical efficiency as an indicator of agricultural production efficiency [34].

There are two main categories of methods to quantify farmers' technical efficiency: non-parametric methods, such as data envelopment analysis (DEA), and parametric methods, such as the stochastic frontier analysis method (SFA) [32]. Compared to the DEA method, the SFA method has two main advantages: First, it allows the error term to be divided into two parts: an inefficiency term and a random error term, enabling an accurate description of agricultural production inputs [21]. Second, the SFA method estimates a stochastic production frontier, which can effectively avoid the impact of natural disasters and weather changes on technical efficiency estimation [35]. This study therefore used the SFA method to measure farmers' technical efficiency.

The SFA method requires setting a functional relationship between inputs and outputs [36]. The commonly used functional forms are the transcendental logarithmic production function and the Cobb–Douglas (C–D) production function [37]. Compared to the transcendental logarithmic production function, the C–D production function is more concise and its economic meaning is easier to understand. Moreover, the focus of this section is on measuring farmers' technical efficiency, not on examining the form of the production function. Based on Christensen et al. [37], the C–D production function yields better results than other functional forms. In addition to the Cobb–Douglas (C–D) frontier, we also estimated a translog specification as a flexible alternative. Since the C–D model was nested within the translog model, we formally tested the joint null hypothesis that the second-order and interaction terms in the translog function were jointly equal to zero (i.e., the C–D restrictions). The test results suggested that the translog form did not yield a statistically significant improvement in model fit relative to the C–D form. We therefore retained the C–D production frontier as the baseline for technical-efficiency estimation. Nevertheless, we note that functional-form choice may affect the level and dispersion of estimated efficiency; reassuringly, our qualitative conclusions regarding the efficiency effect of GPCT adoption are robust to using the alternative functional form.

This study therefore adopted the C–D production function form to measure farmers' technical efficiency. Following Battese et al. [36], the C–D form of the SFA method was specified as follows:

$$\ln Y_i = \alpha_0 + \alpha_1 \ln L_i + \alpha_2 \ln T_i + \alpha_3 \ln K_i + \vartheta_i - \mu_i \quad (1)$$

In Equation (1), Y_i represents the apple output of the *i-th* farmer, while L_i, T_i, and K_i are the labor, land, and capital input factors, respectively. α_0, α_1, α_2, and α_3 are the parameters to be estimated, and ϑ_i is the random error term, assumed to follow a symmetric normal distribution. The inefficiency term μ_i follows an exponential distribution with a mean of λ. The stochastic frontier production function was estimated using Maximum Likelihood Estimation (MLE), and the technical efficiency of farmers could be calculated as follows:

$$TE_i = E(Q_i|u_i, X_i)/E(Q_i|u_i = 0, X_i) \quad (2)$$

where $E(Q_i|u_i, X_i)$ is the expected output of the farmer and $E(Q_i|u_i = 0, X_i)$ is the maximum expected output. The technical efficiency of farmers was defined as the ratio of the actual output to the maximum output. The value of technical efficiency ranged from 0 to 1, with values closer to 1 indicating that farmers were near maximum efficiency and values closer to 0 indicating greater inefficiency.

Technical efficiency measures the management and production efficiency of farmers [32]. Based on the existing literature [38,39] and the theory of farmer behavior, this study selected factors such as the adoption of green pest control technologies, the characteristics of production decision-makers, household characteristics, and agricultural production characteristics as factors influencing agricultural production technical efficiency. To exam-

ine the impact of green pest control technology adoption on farmers' technical efficiency, the following preliminary model was proposed:

$$TE_i = \beta_0 + \beta_1 GPCT_i + \sum_{j,i}^{m,n} \beta_j X_i + \varepsilon_i \quad (3)$$

In Equation (3), $GPCT_i$ represents whether the farmer adopts green pest control technology, and X_i is a set of other factors influencing technical efficiency. The random error term ε_i accounts for unobserved factors.

3.1.2. Treatment Effect of Green Pest Control Technology Adoption on Farmers' Technical Efficiency: Endogenous Switching Regression Model

While the SFA method estimates farmers' technical efficiency, this section further analyzes the effect of green pest control technology adoption on farmers' technical efficiency. In practice, apple farmers make the decision to adopt green pest control technology, and the choice of treatment and control groups is not random, which may introduce selection bias. Existing studies often use propensity score matching (PSM) methods to assess the impact of treatment variables on farmers' technical efficiency [40–42]. However, PSM is a non-parametric method and can only address selection bias caused by observable factors. The endogenous switching regression model (ESR) can address both observable and unobservable factors that may lead to selection bias [43]. Based on existing research [44], this study therefore selects farmers' technical efficiency as the outcome variable and green pest control technology adoption as the treatment variable, using the ESR model to empirically test the impact of green pest control technology adoption on farmers' technical efficiency.

The ESR model regression process consists of two steps: first, selection equation regression, which reflects the relationship between various variables such as personal characteristics, household production management, and the decision to adopt green pest control technology [43]; second, outcome equation regression, which estimates the impact of green pest control technology adoption on farmers' technical efficiency, controlling for endogeneity [19].

The first-stage selection equation and the second-stage outcome equation were as follows.

Selection Equation:

$$GPCT_i^* = \delta X_i + \partial I_i + \varepsilon_i, GPCT_i = \begin{cases} 1, if.GPCT_i^* > 0 \\ 0, if.GPCT_i^* \leq 0 \end{cases} \quad (4)$$

Outcome Equation for Treatment Group:

$$TE_{1i} = \beta_1 X_{1i} + \sigma_1 \lambda_{1i} + \tau_{1i} \quad (5)$$

Outcome Equation for Control Group:

$$TE_{0i} = \beta_0 X_{0i} + \sigma_0 \lambda_{0i} + \tau_{0i} \quad (6)$$

In the selection equation, $GPCT_i$ is a binary variable that indicates the decision to adopt green pest control technology, determined by the utility gained from adopting versus not adopting. The random error terms ε_i and τ_i were assumed to be normally distributed. The outcome equations represented the technical efficiency of farmers in the treatment and control groups. The model used the inverse Mills ratio from the selection equation to address selection bias caused by unobserved factors.

The ESR model was estimated using Maximum Likelihood Estimation (MLE), which jointly estimates the selection and outcome equations. The average treatment effect on the

treated (ATT) and the average treatment effect on the untreated (ATU) could be calculated using the following expressions (7) and (8):

$$ATT = E(TE_{1i}|GPCT_i = 1) - E(TE_{0i}|GPCT_i = 1) \quad (7)$$

$$ATU = E(TE_{1i}|GPCT_i = 0) - E(TE_{0i}|GPCT_i = 0) \quad (8)$$

The ESR model allowed us to address potential selection bias and provide more accurate estimates of the treatment effect of GPCT adoption on technical efficiency.

3.2. Data Source

The micro-level data for this study was collected in 2022 through a questionnaire survey targeting apple farmers in the primary apple-producing regions around the Bohai Sea. The surveyed areas included Muping District, Penglai District, and Qixia City in Yantai, Shandong Province, as well as Mengyin County and Yishui County in Linyi. The survey employed one-on-one questionnaire interviews and utilized stratified sampling to account for regional economic development levels, agricultural production scales, and geographical characteristics.

In each county or district, two to three townships were selected, followed by the selection of two to three administrative villages within each township. Within each village, 10 to 20 apple farmers were randomly chosen for one-on-one interviews and questionnaire surveys. A total of 475 questionnaires were distributed, of which 409 were valid, yielding an effective response rate of 86.11%. Specifically, a questionnaire was considered valid if it (i) was fully completed for the core modules, (ii) contained non-missing values for the key variables required for the SFA method and ESR model estimations (output, labor input, land input, pesticide and fertilizer input, other capital input, GPCT adoption indicator, the instrumental variable, and main covariates), and (iii) passed basic logical and consistency checks (e.g., non-negative costs and output; positive cultivated area; no internally contradictory responses). Questionnaires failing any of these criteria were excluded.

In the surveyed apple orchards, farmers' GPCT was implemented not only through physical/ecological measures (e.g., trapping and monitoring-based decisions) but also through the use of biopesticides and agricultural antibiotics. Based on field interviews and farmers' reports, commonly used products in the biological/green control package included abamectin 1.8% EC (such as Shandong Qilu Pharmaceutical Co., Ltd., Jinan, China), polyoxin B 10% WP, locally referred to as duokangmeisu (such as Shandong Lvba Pesticide Co., Ltd., Jinan, Shandong, China), and jinggangmycin/validamycin A 5% AS (such as Shandong Huayang Technology Co., Ltd., Tai'an, China). In addition, some adopters applied selective insect growth regulators, such as hexaflumuron 5% EC (Shandong Zibo Lüjing Pesticide Co., Ltd., Zibo, China), a benzoylurea chitin-synthesis inhibitor, as complementary tools under IPM-aligned management.

To address application intensity, we also collected the number of pesticide spray applications per year. Across 409 households, the median number of applications was 8 (interquartile range: 8–10), with the 95th percentile at 13 and the 99th percentile at 15 applications. Table 1 reports the results of a two-sample *t*-test with equal variances for the number of pesticide spray applications per year. Group Non-Adopters refers to non-adopters of GPCT and Group Adopters refers to adopters of GPCT. The *p*-value from the two-tailed *t*-test was 0.568, indicating no statistically significant difference between the two groups.

Table 1. Two-sample *t*-test on pesticide spray applications.

Group	Number	Mean	Std. Error	Std. Deviation	95% Confidence Interval	*p*-Value (Two-Tailed)
Non-Adopters	186	10.33	1.58	21.58	[7.21, 13.45]	0.568
Adopters	223	9.50	0.14	2.06	[9.23, 9.77]	
Combined	409	9.88	0.72	14.62	[8.45, 11.30]	
Difference		0.83	1.45		[−2.03, 3.69]	0.568

Data Source: Calculated using Stata 17 based on survey data.

3.3. Variable Selection

To capture the relevant factors affecting farmers' technical efficiency and the adoption of GPCTs, we selected the following key variables:

3.3.1. Input and Output Variables

The output variable was the total income from apple cultivation, calculated by multiplying the output level of different apple varieties produced by the apple farmers by their respective sales prices. The labor input variable was the total labor input in all stages of apple cultivation, including both family labor and hired labor. The land input variable refers to the total area of land used for apple cultivation. The pesticide and fertilizer capital input variable was the total cost of pesticides and fertilizers used in the apple cultivation process. The non-pesticide fertilizer capital input variable represented the total production costs, including expenses for orchard management tools, grafting and scion costs, bagging and harvesting labor costs, refrigeration, water, electricity, and irrigation costs.

It is worth noting that the input–output variables were primarily used to measure the technical efficiency of apple farmers. In this study, we used the Cobb–Douglas (C–D) production function form in the stochastic frontier production function model to calculate efficiency, and the input–output variables were expressed in logarithmic form in the model. Therefore, the variable definitions for input–output also adopted logarithmic forms.

As a measure of pesticide input intensity, we collected data on the number of pesticide spray applications per year across the surveyed farms. A two-sample *t*-test comparing the spray application frequencies between adopters and non-adopters of GPCT revealed no significant difference (*p*-value = 0.568) between the two groups. The average number of applications for non-adopters was 10.33, while for adopters it was 9.50 (Table 1). This indicates that while GPCT adoption might be linked to a potential reduction in pesticide spray intensity, the difference was not statistically significant in our sample.

3.3.2. Outcome Variable: Farmers' Technical Efficiency

This variable was derived from the estimation of the C–D production function form using the stochastic frontier production function model.

3.3.3. Treatment Variable: Green Pest Control Technology Adoption Decision

Our GPCT adoption variable was defined as a binary indicator equal to one if a farmer adopted at least one practice from the GPCT set during the production season. As a result, the ESR-based ATT/ATU estimates needed to be interpreted as the average technical-efficiency effect of 'any GPCT adoption' versus none. If returns differed across GPCT components (or across adoption intensity), the estimated effect represented a weighted average across the observed adoption mix and could mask component-specific impacts; this heterogeneity was not separately identified in the current framework and is discussed as a limitation and a direction for future research.

While this binary specification is parsimonious and closely aligned with policy discourse on 'GPCT adoption' as initial uptake, it does not capture heterogeneity in adoption intensity (e.g., the number of GPCT components adopted, usage frequency, or the magnitude of input reallocation) or specific technology bundles. Constructing an intensity-based measure or composite index would require comparable cardinal information across heterogeneous practices and a defensible weighting scheme, which was not directly available from our survey and could have introduced additional measurement error and arbitrariness. We therefore interpreted our estimates as the average effect of any GPCT adoption versus none.

As a diagnostic for the exclusion restriction, we additionally included the distance variable in the technical-efficiency outcome equations; the coefficient was statistically insignificant ($p > 0.10$), and the estimated efficiency effects of GPCT adoption were virtually unchanged.

3.3.4. Control Variables

Based on the existing literature [24,45–49], the following control variables were selected for this study:

(1) Personal characteristics of the surveyed farmers, including variables such as age, education level, years of apple cultivation experience, and the square of years of cultivation.
(2) Household production and management characteristics, including variables such as the number of agricultural training sessions attended, per capita apple farming area, and number of people involved in farming.
(3) Orchard conditions, including variables such as the fragmentation degree of the orchard and soil quality.

Additionally, to exclude the interference of regional characteristics, economic levels, and other factors, the model also included a set of regional dummy variables.

3.3.5. Instrumental Variables

To address potential endogeneity issues, such as measurement errors or omitted variables in the empirical regression process, instrumental variables were required. This study selected the variable "distance from the residence to the nearest green production technology promotion location" as the instrumental variable. This variable significantly influenced apple farmers' decision to adopt green pest control technologies, but it was exogenous to farmers' technical efficiency, making it suitable as an instrumental variable for the model.

The underlying intuition was that proximity increases farmers' exposure to GPCT demonstrations and trainings and lowers travel and participation costs, which affects the adoption decision. The exclusion restriction required that, conditional on observed household characteristics, farm inputs, and location controls, this distance measure did not directly influence farmers' technical efficiency except through its impact on GPCT adoption. Potential direct channels include broader access to markets, infrastructure, and general extension services. To address these concerns, we controlled for location-related factors capturing market/extension access (e.g., distance to township/county center, road/infrastructure conditions, and village characteristics where available) and conducted a robustness check by allowing the distance variable to enter the outcome equations; it was statistically insignificant and the estimated ATT/ATU results remained qualitatively unchanged.

3.4. Descriptive Statistical Analysis

Table 2 reports the variables used in the empirical analysis of this study, along with their definitions and descriptive statistics. Analyzing the contents of the table reveals

that 223 of the respondents, approximately 54.52% of the total sample, adopted green pest control technologies in their apple cultivation process, while the remaining 186 respondents, or approximately 45.48%, did not adopt these technologies. The mean of the farmers' technical efficiency was 0.70, indicating a 30% efficiency loss. The average age of the respondents was 55.23 years, with an average education level of 8.11 years. The average years of apple cultivation experience was 21.74 years. The mean distance between the respondents' residences and the nearest green technology promotion location was 6.07 km.

Table 2. Variable definitions and descriptive statistics.

Category	Variable	Definition (Short)	Unit	Transformation (Used in Estimation)	Mean	Standard Deviation
Output	Total Output	Total income from apple cultivation (2020)	CNY 10,000 (approximately equal to USD 1420)	ln(·)	6.93	7.61
Input	Labor Input	Total labor input (2020)	workdays	ln(·)	167.49	239.54
Input	Land Input	Total area of apple cultivation (2020)	Mu	ln(·)	6.29	6.76
Input	Pesticide and Fertilizer Input	Expenditure on pesticides and fertilizers (2020)	CNY 10,000 (approximately equal to USD 1420)	ln(·)	1.79	2.87
Input	Other Capital Input	Other capital input (2020)	CNY 10,000 (approximately equal to USD 1420)	ln(·)	1.03	2.38
Outcome	Technical Efficiency	Estimated by SFA method	(unitless)	Level	0.7	0.1
Treatment	Green Pest Control Adoption	Yes = 1, No = 0	-	Dummy	0.54	0.5
Controls	Age	Respondent age	years	Level	55.23	9.85
Controls	Education Level	Years of education	years	Level	8.11	2.79
Controls	Cultivation Experience	Years of apple cultivation	years	Level	21.74	11.82
Controls	Square of Cultivation Experience	(Experience^2)/100	-	Squared (/100)	6.12	7.34
Controls	Agricultural Training	Training sessions (past 3 years)	sessions	Level	2.2	1.56
Controls	Number of Farmers	Household members in apple farming	persons	Level	2.49	0.9
Controls	Per Capita Operating Area	Area per person	Mu/person (approximately equal to 0.165 acre/person)	Level	2.3	2.61
Controls	Fragmentation Degree	Parcels per Mu	parcels/Mu (approximately equal to parcels/0.165 acre)	Level	0.65	0.52
Controls	Soil Quality	1 = poor, 2 = average, 3 = good	-	Ordinal	2.19	0.58
Controls	Regional Dummy	Yantai = 1, Linyi = 0	-	Dummy	0.38	0.48
IV	Distance to Promotion Location	Distance to nearest green-tech promotion site	km	Level	6.07	4.84

Data Source: Compiled from survey data. Notes: For regression/SFA estimation, selected continuous variables were natural-log transformed as indicated in the "Transformation" column. Reported Mean and Standard Deviation were computed in the original units (levels).

4. Empirical Results of the Impact of Green Pest Control Technology Adoption on Farmers' Technical Efficiency

4.1. Estimation Results of Farmers' Technical Efficiency

The overall distribution of farmers' technical efficiency estimates, as well as the distribution within the treatment and control groups, is reported in Table 3. Columns 2–3, 4–5, and 5–7 report the efficiency distributions for the total sample, treatment group, and control group, respectively. It can be observed that there were several differences between the treatment and control groups:

Table 3. Distribution of farmers' technical efficiency estimation results.

Efficiency Interval	Total Sample		Treatment Group Farmers		Control Group Farmers	
	Sample Size	Percentage (%)	Sample Size	Percentage (%)	Sample Size	Percentage (%)
[0.1–0.5)	42	10.27	7	3.14	35	18.82
[0.5–0.7)	103	25.18	53	23.77	50	26.88
[0.7–0.8)	198	48.41	123	55.15	75	40.54
[0.8–1)	66	16.14	40	17.94	26	13.76
Maximum Value	0.946		0.917		0.946	
Minimum Value	0.187		0.387		0.187	
Mean	0.708		0.739		0.669	
Sample Size	409		223		186	

Data Source: Farmers' technical efficiency values are estimated from the C–D form of the stochastic frontier production function model.

First, the mean technical efficiency of the total sample was 0.708, indicating a 29.2% efficiency loss. The mean technical efficiency for farmers in the treatment group was 0.739, indicating a 26.1% efficiency loss, while the mean technical efficiency for farmers in the control group was 0.671, indicating a 32.9% efficiency loss. This shows that there was still room for improvement in the farmers' technical efficiency.

Second, the technical efficiency for the total sample ranged between 0.187 and 0.946. For the treatment group, the technical efficiency ranged between 0.387 and 0.917, while for the control group, the efficiency also ranged between 0.187 and 0.946. This indicates that there was significant variation in technical efficiency among the sample farmers. Notably, the minimum value and mean technical efficiency of the treatment group were both higher than those of the control group. However, this alone did not allow us to conclude that the efficiency difference was due to the adoption of green pest control technologies. To verify the impact of green pest control technology adoption on farmers' technical efficiency, further empirical analysis was needed. Specifically, to credibly identify the effect of GPCT adoption while accounting for self-selection and endogeneity, the following section describes an ESR framework complemented by multiple robustness checks. In addition, robustness checks using alternative technical-efficiency estimation approaches (e.g., comparing SFA and DEA or varying distributional assumptions) and heterogeneity analyses across farm sizes, crops, and regions would strengthen the credibility of the findings.

4.2. Analyzing the Impact of Green Pest Control Technology Adoption on Farmers' Technical Efficiency

4.2.1. Joint Estimation of Green Pest Control Technology Adoption and Farmers' Technical Efficiency Using the ESR Model

The joint estimation results of green pest control technology adoption and farmers' technical efficiency are shown in Table 4. In columns 2 and 3, the estimation results for the factors influencing green pest control technology adoption are reported, while columns 4–5 and 6–7 provide the estimation results for the factors influencing farmers who adopted and did not adopt green pest control technologies. From the table, it can be observed that there were several differences between the treatment and control groups:

Table 4. ESR model results for the impact of green pest control technology adoption on farmers' technical efficiency.

Variable	Selection Equation		Outcome Equation: Non-Adopters		Outcome Equation: Adopters	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Age	0.020 **	(0.010)	0.000	(0.001)	−0.001	(0.001)
Education Level	0.079 ***	(0.027)	0.001	(0.004)	−0.003	(0.002)
Years of Cultivation	−0.016	(0.019)	0.006 ***	(0.002)	0.003 **	(0.001)
Square of the planting years	0.022	(0.025)	−0.009 **	(0.004)	−0.003 *	(0.002)
Technical Training	0.075	(0.061)	0.007	(0.010)	−0.001	(0.003)
Number of Farmers	0.007	(0.118)	−0.004	(0.013)	−0.008	(0.008)
Per Capita Operating Area	−0.023 *	(0.044)	0.009	(0.006)	−0.003 *	(0.002)
Fragmentation Degree	−0.375 **	(0.171)	−0.037 **	(0.016)	0.026 *	(0.014)
Soil Quality	−0.083	(0.154)	0.008	(0.019)	0.018 **	(0.008)
Regional Dummy Variable	Controlled		Controlled		Controlled	
Distance to Promotion Location	−0.066 ***	(0.017)				
Constant	−1.323 *	(0.769)	0.608 ***	(0.099)	0.835 ***	(0.055)
Test and Other Information						
Log-Likelihood Value	287.49 [0.0395]					
LR Test for Independent Model	20.15 [0.0000]					
Sample Size	409		409		409	

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors and values in brackets represent the *p*-value of the corresponding test.

First, the likelihood ratio (LR) test for the independent model was 20.15, which was statistically significant at the 1% level, rejecting the hypothesis that the selection and outcome equations do not influence each other. This suggests that the two equations should be estimated jointly, making the ESR model a more appropriate choice.

Regarding the instrumental variable test, the Pearson correlation coefficient between the decision to adopt green pest control technology and the distance from the apple farmers' residence to the nearest green production technology promotion location was −0.375, statistically significant at the 5% level. This demonstrates a significant relationship between green pest control technology adoption and the distance from the promotion location. To establish the instrumental variable's validity, a weak instrument test was performed, and the F-statistic was 66.47 (well above 10), eliminating the weak instrument problem. Furthermore, the estimated value for the distance from the residence to the promotion location in columns 2 and 3 of Table 4 is −0.066, statistically significant at the 1% level, indicating that the distance significantly influences the adoption decision of green pest control technologies. The choice of instrumental variable was therefore appropriate.

(1) ESR Model Estimation Results for the Selection Equation

Columns 2 and 3 of Table 4 report the estimation results for the selection equation of the ESR model. It can be seen that age has a significant positive effect on the decision to adopt green pest control technologies. This result is understandable, as older farmers

tend to have more experience and are more likely to adopt various pest control methods, including green pest control technologies, which are considered practical and effective. Additionally, older farmers are less likely to engage in off-farm labor, and they rely more on agricultural production for their livelihood, making them more inclined to invest in better farming practices to improve their income.

Education level also has a significant positive effect on the decision to adopt green pest control technologies. This result is also logical, as farmers with higher education levels are better able to understand the importance of adopting such technologies, which contribute not only to pest control but also to the safety of their products and the environment. Furthermore, these farmers are more likely to adopt and correctly implement green pest control technologies.

Per capita apple farming area has a significant negative impact on the adoption decision. This is because adopting green pest control technologies requires more labor, and farmers with larger per capita farming areas are likely to face more challenges in managing labor inputs. They may therefore avoid adopting green technologies to reduce labor costs.

Fragmentation degree has a significant negative impact on the adoption decision. Smaller and fragmented plots make it harder for farmers to implement detailed management practices and adopt multiple technologies, making them less likely to adopt green pest control methods.

(2) ESR Model Estimation Results for the Outcome Equation

Columns 4–5 and 6–7 of Table 4 report the ESR model estimation results for the outcome equations of farmers who adopted and did not adopt green pest control technologies. The regression results show that the coefficient of years of apple cultivation has a significant positive effect on technical efficiency, while the square of years of cultivation has a significant negative effect. This suggests that the relationship between cultivation experience and technical efficiency follows an "inverted U-shape". As farmers gain more experience, their ability to avoid unnecessary inputs and reduce wastage improves, leading to higher technical efficiency. However, after a certain point, as farmers age and their physical capacity and ability to access new information decline, they may be less willing to change their established practices, negatively impacting technical efficiency.

Per capita apple farming area had a significant negative impact on the technical efficiency of farmers who adopted green pest control technologies. This is because larger farming areas lead to labor shortages, and the increased labor demand associated with green pest control technologies can reduce overall technical efficiency.

4.2.2. Treatment Effects of Green Pest Control Technology Adoption on Farmers' Technical Efficiency

This section evaluates the treatment effects of green pest control technology adoption on farmers' technical efficiency using expressions (7) and (8), the regression results of which are shown in Table 5. It is important to note that the second row in column 2 and the third row in column 3 represent the efficiency levels of apple farmers who actually adopted or did not adopt green pest control technologies. The second row in column 3 and the third row in column 2 represent counterfactual scenarios, where the efficiency values for farmers who adopted green pest control technologies (had they not adopted them), and for farmers who did not adopt green pest control technologies but would have if they had adopted them, are provided.

Overall, the adoption of green pest control technologies had a positive effect on technical efficiency, which was statistically significant at the 1% level. The ATT values indicate that if farmers who adopted green pest control technologies had not adopted them, their technical efficiency would have decreased by 3.9%, from 73.9% to 70.0%. On the

other hand, the ATU results show that if farmers who did not adopt green pest control technologies had adopted them, their technical efficiency would have increased by 18.2%, from 66.8% to 85.1%. These results suggest that adopting green pest control technologies contributes to an increase in farmers' technical efficiency.

Table 5. Average treatment effect of green pest control technology adoption on farmers' technical efficiency.

Farmer Type	Adopted Green Pest Control Technology	Did Not Adopt Green Pest Control Technology	ATT	ATU
Green Pest Control Technology Group	0.739	0.700	0.039 ***	
Non-Adopted Green Pest Control Technology Group	0.669	0.851		0.182 ***

Note: *** represents significance at the 1% level. ATT and ATU represent the average treatment effect for apple farmers who adopted and did not adopt green pest control technology, respectively.

The ATU estimate was notably larger than the ATT, suggesting that current non-adopters would, on average, gain more in technical efficiency under the counterfactual scenario of GPCT adoption. This was also reflected in baseline levels: non-adopters' predicted efficiency under non-adoption was substantially lower than adopters', leaving larger headroom for improvement. A plausible interpretation is that non-adopters have lower baseline efficiency and therefore more room for 'catch-up' once GPCT-related practices improve pest-management effectiveness and reduce avoidable input waste. In addition, selection into adoption implies that adopters may already possess unobserved managerial ability or complementary assets, so part of their higher observed efficiency is not attributable to adoption per se, resulting in a smaller ATT. Finally, the marginal efficiency gain from GPCTs may be diminishing when farmers are already relatively close to the frontier or have already implemented adjacent IPM-aligned practices. As ATU is a counterfactual average for current non-adopters, realized gains may vary depending on household constraints and complementary capabilities.

4.2.3. Robustness Test

The ESR model is a parametric method for evaluating effects, which heavily relies on instrumental variables. To ensure the robustness of the regression results, this study employs four non-parametric effect evaluation methods: propensity score matching model (PSM), inverse probability weighting model (IPW), regression adjustment model (RA), and inverse probability weighting with regression adjustment model (IPWRA). The results presented in Table 6 show that the ATT values for PSM, IPW, RA, and IPWRA are 0.174, 0.155, 0.176, and 0.155, respectively, all statistically significant at the 1% level. These results confirm that the adoption of green pest control technologies has a positive effect on farmers' technical efficiency, consistent with the earlier findings. It can be concluded therefore that the research results from the baseline regression met the robustness requirements.

Table 6. Robustness test estimation results.

Treatment Variable	Model Type	ATT	Standard Error	t-Value (Z-Value)
Apple Farmers' Agricultural Production Technical Efficiency	PSM	0.174 ***	0.037	4.70
	IPW	0.155 ***	0.033	4.65
	RA	0.176 ***	0.039	4.49
	IPWRA	0.155 ***	0.033	4.65

Note: *** represents significance at the 1% level. Additionally, the PSM model reports the results from the one-to-one matching method.

5. Discussion

This study provides evidence that adopting GPCTs—which largely overlap with key components of IPM, such as monitoring-based decision making, biological/physical control, and reduced reliance on broad-spectrum chemicals—can improve apple farmers' technical efficiency. Beyond confirming an efficiency-enhancing association after addressing self-selection, our findings help interpret why GPCTs may raise efficiency, for whom the gains are the most significant, and what this implies for sustainable fruit production.

5.1. Efficiency Gains in the Context of International Evidence

Our finding that GPCT adoption improves technical efficiency is broadly consistent with the international IPM literature emphasizing that knowledge- and monitoring-based pest management can reduce pesticide use and costs without necessarily sacrificing yield outcomes. For example, threshold-based (action-threshold) pest management—an IPM cornerstone—has been shown in multi-crop evidence syntheses to cut insecticide applications and associated costs while maintaining overall yield relative to calendar spraying [50,51]. In apple systems specifically, a global meta-analysis indicates that IPM adoption tends to enhance natural-enemy performance and reduce pest/disease pressure, though yield effects can be context-dependent and sometimes negative, while quality may be maintained [52].

Importantly, empirical studies from multiple regions also suggest that IPM-related transitions can translate into measurable efficiency or productivity improvements when they reduce redundant chemical use and improve decision timing. Frontier-based evidence from South Asia, for instance, finds significantly higher technical efficiency among IPM adopters after accounting for self-selection into adoption [11]. In Latin America, selection-corrected stochastic frontier estimates similarly indicate higher technical efficiency in areas with more intensive biological pest control use [22]. Complementary European evidence highlights substantial inefficiency/overuse in pesticide (damage-control) inputs, implying scope to reduce chemical inputs without reducing output—an empirical pattern consistent with the "precision and input-saving" logic of IPM/GPCT approaches [53]. Recent FADN-based efficiency analyses further show that sustainability-oriented "ecologization" indicators (e.g., crop diversification and related management shifts) can be statistically linked to technical efficiency, underscoring that environmental management changes can carry real performance consequences in commercial agriculture [54]. Evidence from sub-Saharan Africa also emphasizes that impacts can be component-specific: after correcting for selection, some IPM elements are associated with improved yields and/or net returns, while others may not uniformly raise output—highlighting that the performance effects depend on which practices are adopted and how they are implemented [55]. Taken together, this international evidence supports the interpretation that "better pest management" does not automatically increase yields everywhere, but it can still improve the efficiency with which farmers convert inputs into outputs—especially when chemical inputs become more targeted and less wasteful.

Our results also connect with the emerging empirical literature on GPCTs in China's apple sector. Recent studies report that GPCT adoption can reduce pesticide-use intensity [24] and generate income gains—particularly among lower-income farmers—through improved pest management and production performance [7]. By focusing on technical efficiency rather than only yield or income, this study adds a complementary sustainability-relevant performance metric and helps explain how "green" pest-control transitions may contribute to sustainable intensification.

5.2. Plausible Mechanisms: Input-Saving, Precision, and Managerial Upgrading

The efficiency advantage for GPCT adopters likely operates through at least three channels. First, GPCTs encourage more precise pest control (e.g., monitoring and timing), reducing unnecessary applications and thereby lowering input redundancy—an efficiency pathway consistent with evidence that action-threshold strategies reduce chemical use while keeping crop output broadly stable [51]. Second, substituting part of conventional pesticides with biological or physical methods may mitigate resistance-driven "pesticide treadmill" dynamics and improve the stability of pest suppression, which is frequently highlighted as a key motivation for IPM-type transitions [52,56]. Third, adoption may proxy a broader "managerial upgrade": GPCT adopters often participate in training, learn scouting/diagnostics, and improve on-farm decision making. This interpretation aligns with farm-level evidence that IPM training and practice can be associated with higher technical efficiency for vegetable growers [11].

At the same time, international reviews emphasize that IPM/GPCT is knowledge-intensive and adoption can be constrained by information gaps, perceived risks, and limited institutional support [56]. Recent evidence from China similarly indicates that information awareness and social networks can play important roles in shaping GPCT adoption decisions [9]. These insights help interpret why, even when GPCTs are efficiency-enhancing, diffusion may remain incomplete without effective extension and learning mechanisms.

5.3. The Reason Why Lower-Income Farmers Gain More

The larger efficiency gains among lower-income farmers suggest an "inclusive" potential of GPCTs. One plausible explanation is diminishing marginal returns via management improvements: farmers operating closer to best-practice frontiers (often better-resourced farmers) may have less room for additional efficiency gains, whereas constrained farmers may benefit more from improved targeting and reduced waste. This pattern is consistent with recent evidence from China's apple sector showing that GPCT-related income gains can be stronger for lower-income farmers [7]. It also echoes impact-evaluation findings in other contexts where training and better pest management practices disproportionately improve performance among farmers with weaker initial access to information [11].

From a policy perspective, this heterogeneity matters: if GPCTs deliver larger marginal efficiency returns for disadvantaged groups, then well-designed support programs can jointly advance environmental objectives and rural equity, rather than creating trade-offs between "green" and "inclusive" development.

5.4. Implications for Policy and Future Research

Three implications follow. First, extension systems should prioritize practical, field-based learning (scouting, thresholds, diagnosis, and safe/targeted control) to lower the knowledge barrier that IPM reviews identify as a persistent constraint [56]. Second, to accelerate adoption among resource-constrained farmers, complementary measures—such as targeted training subsidies, demonstration orchards, and risk-sharing instruments—may be warranted, especially because evidence suggests that lower-income farmers may reap larger benefits [7]. Third, policy frameworks that clarify implementation standards, monitoring, and evaluation can improve credibility and uptake of IPM-like approaches across regions; comparative analyses of IPM governance highlight the importance of coherent implementation and accountability mechanisms [57].

One limitation is that the substitution and optimization mechanisms in Figure 1 were not directly tested in the current empirical setup. While the ESR estimates provide credible evidence on the overall efficiency effect of GPCT adoption, identifying specific channels would require additional information on component-level adoption and management

intensity (e.g., pesticide quantities/cost shares, labor allocation, scouting frequency, and threshold-based decision rules). Future work with richer data could empirically decompose the efficiency gains across these channels. A further limitation concerns the measurement of GPCT adoption. Because our treatment variable was binary, the estimated ATT/ATU effects represent an average across adopters with potentially different adoption intensities and technology combinations. If marginal returns vary with intensity or bundles, our estimates may mask such nonlinearities and compositional heterogeneity. Collecting consistent component-level intensity measures (e.g., quantities/cost shares, frequency of use, and monitoring effort) would allow future research to estimate dose–response relationships and identify the most efficiency-enhancing GPCT bundles.

Finally, further empirical work could strengthen causal interpretation and unpack mechanisms more directly. Future research could (i) use panel data or repeated surveys to assess dynamic efficiency effects and learning trajectories, (ii) integrate more detailed measures of GPCT intensity (e.g., scouting frequency, threshold use, biocontrol adoption) to test which components drive efficiency gains, and (iii) explore whether the efficiency effect varies with pest pressure, ecological conditions, or market/quality requirements—an issue suggested by the context-dependent outcomes observed in global apple IPM evidence [52].

6. Conclusions

GPCT adoption significantly improves technical efficiency, with non-adopters potentially experiencing an 18.2% increase in efficiency if they adopt these technologies. Conversely, adopters would face a 3.9% decline in efficiency if they discontinued their use. Additionally, the efficiency gains from GPCT adoption are greater for lower-income farmers, suggesting that these technologies can help reduce efficiency disparities among different income groups.

These findings highlight the importance of supporting the adoption of GPCTs, particularly for resource-constrained farmers, through targeted policies such as financial assistance, subsidies, and enhanced access to agricultural extension services. These measures can help overcome barriers to adoption and foster sustainable agricultural practices. Policymakers should also consider market-driven incentives, such as premium prices for sustainably produced apples and certification schemes, to further encourage adoption.

While this study provides valuable insights, it is limited by its focus on apple farmers in Shandong Province, China. Future research could expand to other regions and incorporate broader ecological and health impact measures, as well as explore the psychological and behavioral factors influencing adoption decisions.

In conclusion, this study demonstrates that GPCT adoption can enhance technical efficiency and promote sustainable agricultural practices, especially among lower-income farmers. Policymakers should therefore prioritize promoting these technologies to achieve both economic and environmental sustainability goals.

Beyond reiterating the estimated treatment effects, our results have broader implications for sustainable horticulture. In perennial orchard systems characterized by high pest and disease pressure, GPCT adoption can contribute to sustainable intensification by improving the efficiency with which labor, land, and purchased inputs are transformed into output, while potentially reducing the environmental footprint associated with conventional chemical control. The finding that non-adopters would experience sizable counterfactual efficiency gains also implies substantial unrealized productivity potential, highlighting the importance of lowering learning and information barriers in the diffusion stage.

Although the empirical evidence is based on apple producers in China, the efficiency-enhancing role of knowledge-intensive pest-management practices may extend to other horticultural crops and regions where similar constraints hold. At the same time, external

validity likely depends on complementary conditions such as the availability of GPCT inputs, the capacity of local extension systems, and farmers' access to training and output markets. Given that our analysis uses a binary adoption measure and cross-sectional data, future research combining multi-region panel datasets with component-level intensity measures could examine longer-run dynamics, identify dose–response relationships, and determine which GPCT bundles deliver the largest and most inclusive efficiency gains.

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Abbreviations

The following abbreviations are used in this manuscript:

GPCT	Green Pest Control Technology
GPCTs	Green Pest Control Technologies
IPM	Integrated Pest Management
SFA	Stochastic Frontier Analysis
ESR	Endogenous Switching Regression
PSM	Propensity Score Matching
IPW	Inverse Probability Weighting
RA	Regression Adjustment
IPWRA	Inverse Probability Weighting with Regression Adjustment

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