

Article

Heterogeneous Effects of Conservation Tillage Practices on Farmers' Fertilizer Use Efficiency: Evidence from Wheat–Maize Systems in China

Boqian Wang, Yu Wang and Xiuguang Bai * 

College of Economics and Management, Northwest A&F University, Yangling 712100, China; wbq975077172@nwfau.edu.cn (B.W.); wangycc123@nwsuaf.edu.cn (Y.W.)

* Correspondence: baixg960@nwsuaf.edu.cn

Abstract

Excessive fertilizer use threatens soil quality and the sustainability of grain production, making improvements in fertilizer use efficiency (FUE) essential. This study examines how conservation tillage (CT) practices affect FUE in China's wheat–maize rotation system using survey data from 1528 farm households in Shandong, Henan, Anhui, Shaanxi, and Shanxi provinces of China. We estimate FUE using stochastic frontier analysis (SFA) and identify the treatment effects of tillage choices using a multinomial endogenous switching regression (MESR) model to correct for self-selection. Three tillage practices are compared: conventional rotary tillage with straw returning (CTS), no-tillage with straw returning (NTS), and deep tillage with straw returning (DTS). The results show that the average FUE of farmers in grain production in the sample area is 0.5045 and displays a bimodal distribution. Relative to CTS, NTS significantly improves farmers' FUE, whereas DTS significantly reduces it. Mechanism analysis indicates that NTS improves FUE through both reduced fertilizer input and increased yield, while DTS mainly increases yield without reducing fertilizer input. Threshold analysis further shows that farm size conditions these effects. The findings suggest that CT policies should promote NTS more actively and apply DTS selectively according to farm size and local production conditions.

Keywords: conservation tillage; fertilizer use efficiency; multinomial endogenous switching regression; threshold regression

1. Introduction

Agricultural production underpins economic development and social stability, and grain security remains a central policy concern in many developing countries. In recent years, global food systems have become increasingly vulnerable to external shocks, including geopolitical conflicts, trade disputes, and market volatility, all of which have intensified concerns over food security [1]. In China, the balance between grain supply and demand remains fragile under the combined pressure of population growth and dietary upgrading [2]. At the same time, the long-term intensive use of chemical fertilizers and pesticides has contributed to cultivated land degradation and weakened the productive capacity of arable land, posing a growing challenge to the sustainable development of grain production [3].

As one of the most important inputs in crop production, chemical fertilizer has played a vital role in increasing yields and safeguarding food supply [4]. However, excessive fertilizer application has also led to a series of problems, including soil degradation, declining



Academic Editor: Lorenzo Barbanti

Received: 11 May 2026

Revised: 2 June 2026

Accepted: 10 June 2026

Published: 12 June 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

fertility, low fertilizer use efficiency (FUE), and agricultural non-point source pollution [5], which directly threaten the food security and sustainable development of agriculture in China. Therefore, improving FUE has become essential for reconciling grain production with agricultural sustainability. In this context, conservation tillage (CT) has been widely promoted in China as an important technological pathway for protecting cultivated land quality and improving the agroecological environment. Existing studies suggest that CT can improve soil structure, enhance water retention, promote nutrient cycling, and mitigate land degradation [6]. These potential benefits imply that CT may also affect farmers' FUE. However, whether CT can effectively improve FUE at the farm level remains an open empirical question.

More importantly, CT should be understood as a set of distinct tillage technologies rather than a single farming practice. Different tillage practices, such as conventional rotary tillage with straw returning (CTS), no-tillage with straw returning (NTS), and deep tillage with straw returning (DTS), differ substantially in their operational requirements, agronomic effects, and implications for FUE. Pooling these practices into one broad CT category may therefore mask important differences in their effects on farmers' FUE. Existing studies on CT and FUE are mainly drawn from agronomic field experiments, yet their conclusions remain mixed. Some studies find that CT practices such as no-tillage or straw returning can improve FUE [6,7]. By contrast, other studies report that no-tillage with straw mulching may reduce nitrogen-use efficiency, especially under low-temperature conditions in the early crop growth stage [8]. Still others suggest that the effect of CT on FUE is uncertain or highly context-dependent [9]. These inconsistent findings indicate that the effects of CT on FUE may be highly context-specific and practice-specific.

International evidence also shows that the relationship between conservation tillage and fertilizer-use efficiency is highly context-dependent. In the Indo-Gangetic Plains, conservation agriculture, zero tillage, residue recycling, and improved nutrient management have been widely discussed as strategies for improving productivity and resource-use efficiency under smallholder farming conditions [10,11]. In the US Corn Belt, conservation tillage is more often embedded in large-scale mechanized production systems, where its effects depend on climate, soil quality, irrigation conditions, and nutrient-management practices [12]. These international experiences suggest that conservation tillage does not automatically improve fertilizer efficiency; instead, its effects depend on farm size, machinery access, soil conditions, and complementary fertilizer-management practices. Therefore, examining the heterogeneous effects of different tillage practices in China's wheat–maize system can provide useful evidence for broader debates on conservation agriculture and input-use efficiency.

Although agronomic experiments provide valuable evidence, they often abstract from farmers' actual production and management behavior. As a result, they may have limited ability to capture the farm-level efficiency consequences of tillage adoption under real-world decision-making conditions. By contrast, social science approaches based on household survey data can explicitly account for farmers' behavioral heterogeneity and production constraints. Existing economic studies on CT have examined outcomes such as carbon efficiency and environmental performance [13], but relatively little attention has been paid to farmers' FUE. More specifically, three important gaps remain. First, existing studies rarely examine the effect of CT on FUE using micro-level household data. Second, most studies do not sufficiently distinguish between alternative tillage practices, thereby overlooking possible heterogeneity in FUE effects across CTS, NTS, and DTS. Third, limited evidence is available on the mechanisms through which CT affects FUE and on whether these effects vary across different operational scales.

Using household survey data collected in 2024 from wheat–maize farmers in five provinces of China, this study estimates farmers’ FUE and identifies the effects of different tillage choices while addressing potential self-selection bias. It further explores the underlying mechanisms and threshold heterogeneity across farm-size regimes. This study contributes to the literature in three ways. First, it extends the CT literature by shifting attention from yield, soil, and environmental outcomes to FUE at the farm level. Second, it moves beyond treating CT as a single broad category by explicitly comparing the effects of CTS, NTS, and DTS. Third, by combining treatment-effect estimation, mechanism analysis, and threshold regression, this study provides a more comprehensive understanding of how and under what conditions different tillage practices affect farmers’ FUE. These findings also offer useful implications for the targeted promotion of CT and the improvement of FUE in grain production.

2. Theoretical Framework

2.1. Impact of Tillage Choice on Farmers’ Fertilizer Use Efficiency

Improving FUE is essential for achieving sustainable grain production under increasing resource and environmental constraints. In principle, tillage choice can affect farmers’ FUE through several channels. First, different tillage practices alter soil structure, moisture retention, nutrient cycling, and root growth conditions, thereby influencing fertilizer absorption, nutrient utilization, and ultimately farmers’ FUE [7,14]. Second, tillage practices may affect farmers’ fertilizer input behavior by changing their expectations regarding soil fertility, moisture conservation, and yield stability, which in turn influences the degree of redundant fertilizer application [15,16]. Third, tillage practices may affect crop yield formation, so that the same level of fertilizer input may generate different output outcomes under different tillage regimes [8,9]. Therefore, tillage choice may affect FUE through both input-saving and output-enhancing pathways.

Recent perspectives on precision agriculture and global soil health further help explain how tillage practices may influence FUE through resource optimization. Precision agriculture emphasizes the site-specific matching of fertilizer application with crop demand and soil nutrient conditions through soil testing, crop monitoring, variable-rate fertilization, and data-supported field management [17,18]. From this perspective, improving FUE depends not only on reducing fertilizer input but also on improving the spatial and temporal coordination between fertilizer application, crop uptake, and soil nutrient supply. The global soil health perspective further suggests that reduced soil disturbance, residue retention, improved soil structure, and enhanced biological activity can strengthen nutrient cycling and crop responses to fertilizer input [19]. Therefore, conservation tillage may improve FUE when it is combined with appropriate soil management, fertilizer management, and standardized field operations.

More importantly, CT should not be viewed as a single undifferentiated practice. In this study, farmers’ tillage choices are represented by three distinct practices, namely CTS, NTS, and DTS. Recent meta-analytic and field evidence shows that different tillage methods can generate different effects on crop yield, nitrogen-use efficiency, soil physical conditions, and environmental performance [20,21]. These tillage practices differ substantially in their operational requirements, agronomic implications, and potential effects on FUE. Pooling them into one broad CT category may therefore obscure important heterogeneity in their farm-level efficiency effects.

Compared with CTS, NTS is more likely to improve FUE through two related channels. On the one hand, no-tillage reduces soil disturbance and preserves surface residue cover, which helps retain soil moisture, reduce runoff and nutrient loss, and improve the soil environment for crop growth [22]. On the other hand, the synergistic effect of no-tillage and

straw mulching can reduce material and labor inputs, including chemical fertilizer inputs, while helping cereal crops absorb more essential nutrients such as nitrogen, phosphorus, and potassium from the soil, further increasing yields [23], thereby increasing the FUE [6].

By contrast, the effect of DTS on FUE may be more conditional. Deep tillage can break compacted soil layers, improve soil porosity, and promote root penetration, which may contribute to higher yields, especially where soil compaction constrains crop growth [14]. However, these agronomic benefits do not necessarily imply higher FUE. The effect of DTS on FUE depends more heavily on soil conditions, machinery quality, and field operation standards [24]. When implementation conditions are inadequate, improvements in the plow layer may fail to reduce redundant fertilizer input or translate into more efficient fertilizer use at the farm level [9,25].

Although previous agronomic experiments in China's wheat–maize systems and other grain-producing regions provide useful evidence on the effects of tillage practices on soil moisture, nutrient retention, root growth, fertilizer absorption, and yield response [6,7,22], they are often conducted under relatively controlled field conditions. Such studies may not fully capture farmers' actual production behavior, machinery access, land fragmentation, fertilizer input decisions, and management constraints. By contrast, household-level analysis is better suited to examining the farm-level FUE consequences of tillage choice under real-world decision-making conditions. Based on the above analysis, this study proposes the following hypotheses:

H1. *Compared with CTS, NTS is more likely to improve farmers' FUE.*

H2. *Compared with CTS, DTS does not necessarily improve farmers' FUE, and its effect is conditional on farm size and implementation conditions.*

2.2. Threshold Effect of Tillage Choice on Farmers' Fertilizer Use Efficiency

The effect of tillage choice on farmers' FUE is also likely to depend on farm size. In China, small-scale and fragmented grain production still coexists with more centralized and larger-scale operations [26], and this heterogeneity in operational scale may condition the extent to which alternative tillage practices improve FUE. Small farm size and land fragmentation limit the large-scale use of agricultural machinery such as straw returning and deep tillage [27]. Under such conditions, the potential FUE gains from alternative tillage practices may not be fully realized. As farm size expands, the fixed costs associated with machinery use and field management can be spread more effectively, thereby improving the economic viability of mechanized and standardized tillage practices [28]. Larger-scale farmers are therefore better positioned to implement standardized and mechanized tillage practices, which may strengthen the effects of alternative tillage choices on FUE. In addition, large-scale grain producers are more likely to adopt standardized, highly mechanized and specialized practices [29], which makes it easier for them to implement CT technology mechanically and maximize the benefits, thereby improving FUE. Based on the above analysis, this study proposes the following hypothesis:

H3. *The effect of tillage choice on farmers' FUE exhibits threshold heterogeneity across farm-size regimes.*

3. Materials and Methods

3.1. Econometric Strategy for Identifying the Effects of Tillage Choices on Farmers' FUE

3.1.1. The Multinomial Endogenous Switching Regression Model for Estimating Treatment Effects of Tillage Choices on FUE

In rural China, farmers' choices among conventional rotary tillage with straw return (CTS), no-tillage with straw return (NTS), and deep tillage with straw return (DTS) are not random; rather, they are jointly determined by observable characteristics and unobservable factors. These factors not only shape farmers' tillage choices but may also affect farmers' FUE, thereby giving rise to selection bias and potential endogeneity. Under such circumstances, direct estimation using ordinary least squares (OLS) may produce biased results due to non-random self-selection [30].

Given that the treatment variable in this paper consists of three discrete and mutually exclusive tillage practices, and that both observable and unobservable heterogeneity are involved in farmers' decision-making, this paper employs the multinomial endogenous switching regression (MESR) model as the baseline identification strategy. Through a two-stage estimation procedure, the MESR model corrects for selection bias and allows the construction of counterfactual outcomes and comparable treatment effects across different tillage practices. It therefore provides an appropriate identification framework for evaluating the effects of CT practices on farmers' FUE. The MESR estimation procedure consists of the following stages:

(1) First stage: modeling of farmers' choices

In the first stage, a Multinomial Logit (MNL) model is employed to estimate the probability that farmers choose different tillage practices, thereby characterizing farmers' choice behavior among multiple tillage alternatives and the factors influencing those choices. Since CT is a self-selected decision, heterogeneity in resource endowments, cognitive capacity, and farming conditions across households may render tillage choice non-random. To address this issue, this study treats farmers' tillage choice as the outcome of a latent utility comparison under a random utility maximization framework and constructs selectivity correction terms from the MNL estimates to capture the influence of unobservable factors that may arise during the selection process. Let U_{ij}^* denote the latent utility obtained by farmer i from adopting tillage practice j , such that:

$$U_{ij}^* = \beta_j X_i + \varepsilon_{ij}, j = 0, 1, 2 \quad (1)$$

where X_i is a vector of household and production characteristics, β_j is the parameter vector specific to tillage practice j , and ε_{ij} is the error term. Farmers are assumed to be rational economic agents whose tillage decisions depend on utility differentials. Farmer i chooses tillage practice j if and only if the utility associated with j exceeds that associated with any other alternative regime $k \neq j$. The observed tillage choice is denoted by CT_i , where $CT_i = 0$ represents CTS, $CT_i = 1$ denotes NTS, and $CT_i = 2$ denotes DTS. On this basis, the farmer's decision rule can be expressed as follows:

$$CT_i = \begin{cases} 0, & \text{if } U_{i0}^* > \max_{k \neq 0} (U_{ik}^*) \\ 1, & \text{if } U_{i1}^* > \max_{k \neq 1} (U_{ik}^*) \\ 2, & \text{if } U_{i2}^* > \max_{k \neq 2} (U_{ik}^*) \end{cases} \quad (2)$$

Assuming that the error terms ε_{ij} are independently and identically distributed, the probability that farmer i chooses tillage regime j can be represented by the MNL model as:

$$P_{ij} = \Pr(CT_i = j | X_i) = \frac{\exp(X_i \beta_j)}{\sum_{m=0}^2 \exp(X_i \beta_m)}, j = 0, 1, 2 \quad (3)$$

where P_{ij} denotes the probability that a farmer chooses CTS ($CT_i = 0$), NTS ($CT_i = 1$), and DTS ($CT_i = 2$). Equation (3) is estimated by maximum likelihood, and the resulting estimates are then used to construct the selectivity correction terms required for the second-stage outcome equations.

(2) Second stage: estimating the impact of tillage practices on farmers' FUE

In the second stage, separate outcome equations are specified and estimated for each tillage regime. Since unobservable factors affecting farmers' tillage choices may also influence the farmers' FUE, the outcome equations additionally incorporate the selectivity correction terms derived from the first-stage MNL model. This procedure is intended to correct, as far as possible, for selection bias arising from unobservable factors and thereby improve the reliability of the parameter estimates. Following existing literature [31,32], and abstracting initially from selectivity correction, the outcome equations under the three tillage regimes can be written as follows:

$$\begin{cases} \text{Regime 1 (CTS)} : Y_{i0} = \theta_0 Z_i + \mu_{i0} \text{ if } CT_i = 0 \\ \text{Regime 2 (NTS)} : Y_{i1} = \theta_1 Z_i + \mu_{i1} \text{ if } CT_i = 1 \\ \text{Regime 3 (DTS)} : Y_{i2} = \theta_2 Z_i + \mu_{i2} \text{ if } CT_i = 2 \end{cases} \quad (4)$$

where Y_{ij} ($j = 0, 1, 2$) is the FUE of i -th farmer under tillage regime j ; θ_j is the vector of parameters to be estimated; Z_i is a vector of control variables affecting outcome; and μ_{ij} is the error term.

As noted above, selection bias in tillage choice may arise from both observable and unobservable factors. By including the control variables Z_i , Equation (4) partially accounts for heterogeneity driven by observable factors. Selection bias induced by unobservable factors, however, requires correction through the inclusion of selectivity correction terms. Accordingly, the MESR model further augments the outcome equations by incorporating the selectivity correction terms constructed in the first stage, such that Equation (4) is rewritten as:

$$\begin{cases} \text{Regime 1 (CTS)} : Y_{i0} = \theta_0 Z_i + \gamma_0 \hat{\lambda}_{0i} + \mu_{i0} \text{ if } CT_i = 0 \\ \text{Regime 2 (NTS)} : Y_{i1} = \theta_1 Z_i + \gamma_1 \hat{\lambda}_{1i} + \mu_{i1} \text{ if } CT_i = 1 \\ \text{Regime 3 (DTS)} : Y_{i2} = \theta_2 Z_i + \gamma_2 \hat{\lambda}_{2i} + \mu_{i2} \text{ if } CT_i = 2 \end{cases} \quad (5)$$

where $\hat{\lambda}_{ji}$ denotes the selectivity correction term derived from the first-stage MNL model and captures the magnitude of the correction for selection bias. The coefficient ρ_j represents the correlation between the error terms ε_{ij} and μ_{ij} . Because the generated regressors arising from the two-stage estimation procedure may bias the standard errors, the outcome equations for each tillage regime are estimated separately in the second stage, and robust standard errors are computed using 100 bootstrap replications to mitigate potential heteroskedasticity associated with generated regressors.

(3) Third stage: estimation of the treatment effects

After estimating the outcome equations for the farmers' FUE under different tillage regimes, the treatment effects of alternative tillage practices on farmers' FUE are further derived on the basis of the model-predicted actual and counterfactual outcomes. The analysis focuses primarily on the treatment effects of NTS and DTS relative to CTS. For farmers who actually choose tillage regime j ($j = 1, 2$), the expected FUE under the observed state is given by:

$$E(Y_{ij} | CT_i = j, X_i, \hat{\lambda}_{ji}) = \hat{\theta}_j Z_i + \hat{\gamma}_j \hat{\lambda}_{ji}, j = 1, 2 \quad (6)$$

Based on this, a counterfactual scenario is constructed by assuming that the same farmer, while holding individual characteristics constant, does not adopt NTS or DTS, but instead adopts CTS. The corresponding expected FUE is then:

$$E(Y_{i0}|CT_i = j, X_i, \hat{\lambda}_{ji}) = \hat{\theta}_0 Z_i + \hat{\gamma}_0 \hat{\lambda}_{ji}, j = 1, 2 \quad (7)$$

Accordingly, the Average Treatment Effect on the Treated (ATT) can be defined as:

$$ATT_j = E(Y_{ij}|CT_i = j, X_i, \hat{\lambda}_{ji}) - E(Y_{i0}|CT_i = j, X_i, \hat{\lambda}_{ji}) = (\hat{\theta}_j - \hat{\theta}_0) Z_i + (\hat{\gamma}_j - \hat{\gamma}_0) \hat{\lambda}_{ji}, j = 1, 2 \quad (8)$$

where ATT_1 denotes the ATT of NTS relative to CTS, and ATT_2 denotes the ATT of DTS relative to CTS. In the empirical analysis, the individual-level treatment effects are averaged across the sample to obtain the mean effect differences in NTS and DTS relative to CTS on FUE in grain production. These treatment effects measure how much adopting NTS or DTS changes FUE compared with remaining under conventional rotary tillage, after controlling for both observed and unobserved selection into tillage regimes.

(4) Identification of the instrumental variable

A valid identification of the MESR model requires at least one instrumental variable (IV) that affects farmers' tillage-practice decisions in the first-stage MNL model but does not directly influence FUE in the second-stage outcome equations. Following recent empirical literature on causal identification in observational settings [33], valid IVs must satisfy both the relevance and exclusion restrictions. Based on theoretical considerations and prior empirical evidence, two IVs are employed in this study.

The first IV is whether the household head has participated in training programs related to CT. Participation in such training activities improves farmers' awareness of alternative tillage technologies, increases their knowledge of operational requirements, and enhances their ability to access and implement conservation practices. Prior studies show that agricultural or technology-related training strongly influences technology adoption decisions by reducing information barriers [34]. However, conditional on observed household and production characteristics, the training variable is expected to affect FUE primarily through farmers' adoption of NTS, thereby satisfying the exclusion restriction.

The second IV is perceived benefits, which refers to farmers' perception of whether CT contributes to environmental protection. A growing body of literature demonstrates that farmers' subjective perceptions of environmental benefits shape their willingness to adopt sustainable agricultural practices [35,36]. A stronger belief that CT improves soil health or reduces environmental degradation increases the likelihood of adopting NTS or DTS. Nevertheless, conditional on observed controls, this perception is expected to influence FUE mainly through tillage choice rather than through the technical relationship between fertilizer inputs and crop output. This makes environmental perception an appropriate IV that influences the treatment decision but not the outcome variable.

3.1.2. Model Specification for Mechanism Analysis: Fertilizer-Input and Yield Channels

Based on the mechanisms highlighted in Section 2, we further designed empirical tests to verify how tillage practices affected FUE through specific channels. In particular, we focus on yield and fertilizer input adjustments. To further clarify the transmission mechanism of the impact of tillage practices on the FUE, this paper established the following mechanism test model:

$$YI_i = \alpha_1 + \beta_1 \text{tillage}_i + \gamma \text{contrl}_i + \varepsilon_i \quad (9)$$

$$FI_i = \alpha_2 + \beta_2 \text{tillage}_i + \gamma \text{contrl}_i + \varepsilon_i \quad (10)$$

where YI_i is measured by the total grain yield, and FI_i is the fertilizer input adjustment mechanism, measured by the total fertilizer input. All regressions are estimated using OLS.

3.1.3. Model Specification for Testing Farm-Size Threshold Effects

The impact of CT practices on farmers' FUE may be affected by production scale and may present a nonlinear trend. Therefore, this paper draws on the threshold model and establishes a single-threshold regression model as follows:

$$y_i = \beta_0 + \beta_1 X_i * I(q_i \leq \gamma) + \beta_2 X_i * I(q_i > \gamma) + \theta Z_i + \varepsilon_i \quad (11)$$

where the y_i represents the farmers' FUE, which is calculated using the Stochastic Frontier Analysis (SFA) based method described in Section 3.3.1; the core independent variable X_i represents the adoption decision of tillage practices for farmers, the threshold variable q_i represents the grain production scale of the i -th farmer; Z_i represents the control variables; I is an indicator function; ε_i is the random error term.

3.2. Data Source

The data used in this paper were obtained from a household survey of grain-producing farmers conducted in 2024 across five provinces in China: Shandong, Henan, Anhui, Shaanxi, and Shanxi. The survey targeted farmers engaged in wheat–maize rotation cropping. The sample provinces cover both major and transitional wheat–maize rotation areas in northern China. The five provinces selected for the survey, namely Shandong, Henan, Anhui, Shaanxi, and Shanxi, are representative of China's major wheat–maize rotation systems in terms of both agro-ecological conditions and socio-economic farming structures. Shandong, Henan, and Anhui are located in the Huang-Huai-Hai Plain, one of China's most important wheat–maize double-cropping regions. Shaanxi and Shanxi represent transitional wheat–maize production zones in northern and northwestern China, where rainfall conditions, land fragmentation, mechanization levels, and resource constraints differ from those in the eastern plain areas. Together, these provinces capture substantial variation in climate conditions, farm size, mechanization access, input intensity, and CT adoption, making them suitable for examining the heterogeneous effects of tillage practices on FUE.

The field survey used a combination of multistage and random sampling methods. In each province, 2 to 3 counties or districts were selected based on county-level wheat–maize rotation area, local agricultural production conditions, and consultation with local agricultural authorities. The purpose was to include counties where wheat–maize rotation was common and where conservation tillage adoption varied across farmers. Within each county, 2 to 3 townships were selected from townships with wheat–maize rotation production, considering differences in production conditions, mechanization access, and CT adoption. Within each township, 2 to 3 administrative villages were selected from villages where wheat–maize rotation was practiced. Within each sampled village, 15 to 30 eligible wheat–maize farm households were selected from households identified by local village cadres. Face-to-face interviews were conducted to collect information on various aspects, including individual characteristics of household heads, household income and expenditures, grain-cultivation practices, and awareness and adoption of CT techniques. A total of 1545 questionnaires were collected. After excluding 17 invalid questionnaires, 1528 valid questionnaires remained, yielding a questionnaire validity rate of 98.90%. To ensure the accuracy of farmers' self-reported tillage practices, enumerators provided standardized descriptions of CTS, NTS, and DTS before collecting responses. Farmers were asked about the actual sequence of field operations, including whether straw was returned to the field, whether rotary tillage was conducted, whether direct seeding without rotary tillage was used, whether deep plowing or deep loosening was conducted, and what type of machinery was used. The final classification of CTS, NTS, and DTS was based on these reported field operations rather than solely on farmers' subjective terminology. The household questionnaire has been provided in

Appendix B to allow readers to evaluate the structure of the questions, the definitions of tillage practices, and the measurement of input-output variables.

3.3. Variable Definitions

3.3.1. Dependent Variable: Measurement of Fertilizer Use Efficiency

The dependent variable is the farmers' FUE, which is calculated using the SFA [37]. The methodological foundation of SFA is provided by classic studies such as Battese and Coelli [38] and Reinhard et al. [39]. Recent agricultural economics studies have continued to apply SFA to estimate FUE, fertilizer-reduction potential, and agricultural input-use efficiency, confirming its continued relevance for farm-level efficiency analysis [40,41]. The stochastic frontier production function is typically represented as follows:

$$y_i = f(x_i, \beta) \exp(v_i - u_i) \quad (12)$$

where y_i is the output of the i -th observation, x_i is a vector of inputs including chemical fertilizer, labor, and capital; β is a vector of parameters to be estimated, v_i is a random error, and $v_i \sim iid(0, \sigma_v^2)$; u_i is non-negative inefficiency in the production process, $u_i \sim N^+(m_i, \sigma_u^2)$, and

$$m_i = \delta_0 + \sum_q \delta_q z_q + \omega_i \quad (13)$$

where m_i corresponds to the technical efficiency loss; z_q is the exogenous factor vector affecting the technical efficiency level of the i -th production unit, δ is the parameter vector to be estimated; ω_i is the random error. To estimate the variance components, $v_i - u_i$ is decomposed by maximum likelihood into $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$, rather than separately estimating the random-error variance σ_v^2 and inefficiency variance σ_u^2 . The variance rate γ takes values between 0 and 1. The applicability of the stochastic frontier production function can be checked by calculating the variance rate γ . When γ tends to 1, the productive frontier error is mainly caused by the technical inefficiency term u_i , and the stochastic error v_i plays a small role, and vice versa. Once u_i is estimated, the technical efficiency (TE) of agricultural production TE_i for each production unit in the sample can be estimated by Equation (12) as follows:

$$TE_i = y_i / (f(x_i, t, \beta) \exp(v_i)) = \exp(-\mu_i) \quad (14)$$

It should be noted that the FUE indicator used in this study is not equivalent to general technical efficiency (TE). TE measures the overall distance between observed output and the stochastic production frontier, whereas FUE is an input-specific efficiency indicator that focuses on chemical fertilizer use. Specifically, FUE is defined as the ratio of the minimum chemical fertilizer input required to produce the observed output, conditional on other production inputs, to the actual observed chemical fertilizer input. Therefore, the SFA model is used here to estimate the production frontier, while the FUE indicator is derived by solving for the minimum fertilizer input needed to reach the observed output on that frontier. We use the translog stochastic frontier production function form Bai et al. [37], which is as follows:

$$\begin{aligned} \ln y_i = & \beta_0 + \beta_1 \ln fer_i + \beta_2 \ln la_i + \beta_3 \ln ar_i + \beta_4 \ln wz_i + \beta_5 (\ln fer_i)^2 + \beta_6 (\ln la_i)^2 + \beta_7 (\ln ar_i)^2 + \beta_8 (\ln wz_i)^2 \\ & + \beta_9 \ln fer_i \ln la_i + \beta_{10} \ln fer_i \ln ar_i + \beta_{11} \ln fer_i \ln wz_i + \beta_{12} \ln la_i \ln ar_i + \beta_{13} \ln la_i \ln wz_i \\ & + \beta_{14} \ln ar_i \ln wz_i + v_i - \mu_i \end{aligned} \quad (15)$$

where $i = 1, 2, \dots, n$ denotes the i -th household, y_i represents the household's total grain output from wheat–maize production in one production year, measured in kilograms; fer_i , la_i , ar_i and wz_i are the input variables, which are the amount of chemical fertilizer input,

labor input, land input and other material and service input except chemical fertilizer input. Descriptive statistics for each variable are shown in Table 1.

Table 1. Farm-level input-output variables used to estimate FUE among wheat–maize farmers in five Chinese provinces, 2024.

Indicators	Variables	Mean	Std Dev
Output indicators	Total Grain output (kg)	13,101.1700	79,553.3600
	Chemical fertilizer expenditure (CNY)	5077.6890	27,632.0600
Input indicators	Labor inputs (persons)	2.0007	0.6499
	Land input (ha)	0.8270	4.3541
	Other material expenditure (CNY)	7071.4640	42,115.1100

FUE is defined as the ratio of the minimum chemical fertilizer expenditure required to produce the observed output to the actual chemical fertilizer expenditure. The minimum fertilizer expenditure is not directly observed from the survey; it is derived from the estimated stochastic production frontier by solving for the fertilizer input level required to attain the observed output while holding other inputs constant. It is expressed as follows:

$$FUE = \{ \min[\theta; f(x, \theta fer; \beta) \geq y] \} \leq 1 \quad (16)$$

where $f(x, \theta fer; \beta)$ is the frontier production function; θ is the ratio of the minimum chemical fertilizer input to the actual observed input; x represents the input vector other than chemical fertilizer input; and β is the parameter vector to be estimated. It can be understood that, assuming that there is no technical efficiency loss in the whole production process, the inputs and outputs will all be on the production frontier at this time, and the chemical fertilizer input will be the minimum. Let $\mu_i = 0$, and replace fer_i in Equation (15) with θfer_i , we can obtain

$$\begin{aligned} \ln y_i = & \beta_0 + \beta_1 \ln \theta fer_i + \beta_2 \ln la_i + \beta_3 \ln ar_i + \beta_4 \ln wz_i + \beta_5 (\ln \theta fer_i)^2 + \beta_6 (\ln la_i)^2 + \beta_7 (\ln ar_i)^2 + \beta_8 (\ln wz_i)^2 + \\ & \beta_9 \ln \theta fer_i \ln la_i + \beta_{10} \ln \theta fer_i \ln ar_i + \beta_{11} \ln \theta fer_i \ln wz_i + \\ & \beta_{12} \ln la_i \ln ar_i + \beta_{13} \ln la_i \ln wz_i + \beta_{14} \ln ar_i \ln wz_i + v_i \end{aligned} \quad (17)$$

Subtracting Equation (15) from (17), we obtain:

$$(\beta_1 + \beta_6 \ln la_i + \beta_7 \ln ar_i + \beta_8 \ln wz_i)(\ln \theta fer_i - \ln fer_i) + \beta_5 [(\ln \theta fer_i)^2 - (\ln fer_i)^2] + \mu_i = 0 \quad (18)$$

From the definition of FUE: $\ln FUE_i = \ln \theta = \ln(\theta fer_i / fer_i) = \ln \theta fer_i - \ln fer_i$, then FUE_i is solved as

$$FUE_i = \exp \left\{ \frac{-\lambda_i \pm \sqrt{\lambda_i^2 - 4\beta_5 \mu_i}}{2\beta_5} \right\} \quad (19)$$

where

$$\lambda_i = \frac{\partial \ln y_i}{\partial \ln fer_i} = \beta_1 + \beta_9 \ln la_i + \beta_{10} \ln ar_i + \beta_{11} \ln wz_i + 2\beta_5 \ln fer_i \quad (20)$$

λ_i is the output elasticity of fertilizer in the translog production function, and it is usually assumed that when the production activity is technically efficient, the chemical fertilizer input is also efficient, so Equation (20) only takes a positive root sign. Table 1 reports the farm-level input and output variables used in the stochastic frontier production function. The output variable is total grain output from wheat–maize production in one production year, measured in kilograms. The input variables include chemical fertilizer expenditure, labor input, land input, and other material expenditure. Chemical fertilizer

expenditure and other material expenditure are measured as total farm-level expenditures in Chinese yuan. Labor input is measured as the number of household laborers engaged in wheat–maize production, while land input is measured as cultivated land area. Other material expenditure refers to material costs other than chemical fertilizer costs, including seed costs, pesticide costs, plastic film costs, irrigation costs, and other related non-fertilizer material expenditures. Because the SFA model is estimated at the farm level, total output and total input variables are used, with land input included to control for differences in farm size.

3.3.2. Core Variable

This study focuses on the three tillage practices as the key independent variables, capturing farmers' choices of CT technologies. Three tillage practices are distinguished to reflect different adoption modes. In this study, the three tillage practices are distinguished according to their actual field operations rather than only by farmers' subjective labels. CTS refers to a practice in which crop straw is returned to the field after harvesting, and the soil is subsequently disturbed by rotary tillage before seeding. This practice is widely used in the study area and generally requires common rotary tillage machinery. NTS refers to direct seeding with minimal soil disturbance while retaining straw on or near the soil surface. Compared with CTS, NTS requires specialized no-tillage seeders and better coordination of straw management and seeding operations, but it may reduce soil disturbance, conserve soil moisture, and lower labor and machinery operations. DTS refers to straw returning combined with deep plowing or deep loosening to break compacted soil layers. DTS generally requires higher machinery power, greater fuel and operation costs, and more standardized field operations. Its agronomic effect is more conditional on soil compaction, machinery quality, and operation depth. Therefore, CTS, NTS, and DTS differ substantially in technological requirements, operational sequences, costs, and agronomic implications, which provides an important basis for examining their heterogeneous effects on FUE. CTS is assigned a value of 0. NTS takes a value of 1, while DTS takes a value of 2. In the empirical analysis, CTS is used as the reference category.

In the sample, 55.17% of farmers adopt CTS, 15.05% adopt NTS, and 29.78% adopt DTS. Although the distribution is uneven, each tillage group contains a sufficient number of observations for estimation. This pattern reflects actual adoption differences in the study area, where CTS remains dominant, and NTS adoption is more limited because of its higher technical and machinery requirements. To reduce concerns about the influence of this imbalance, we further conduct robustness checks. This distribution suggests that, although straw incorporation has been widely implemented in the study area, the adoption of CT practices beyond conventional rotary tillage remains relatively limited. By comparing households adopting NTS and DTS with those practicing CTS, this study evaluates the micro-level impacts of different tillage practices on FUE.

3.3.3. Control Variables

Following the existing literature [15,42,43], a set of control variables is included to account for household characteristics and production conditions that may influence FUE. Household-level characteristics include the age of the household head and years of experience in grain cultivation, which capture farmers' human capital and accumulated production knowledge. Household economic capacity is proxied by annual total household income, which may affect farmers' access to machinery services, input purchases, and technology adoption. Production costs are not treated simply as control variables because they are directly related to the construction and mechanism of FUE. Specifically, chemical fertilizer expenditure, labor input, land input, and other material expenditure are

included in the SFA-based FUE measurement, while fertilizer input is further examined as a mechanism variable.

Farm-level production conditions are further accounted for by variables describing infrastructure and land characteristics, including accessibility of field roads, irrigation convenience, soil quality, land fragmentation and the availability of express delivery services. Together, these factors reflect the broader production and logistics environment faced by farmers and are expected to affect FUE by shaping input allocation, mechanization feasibility, and access to agricultural inputs and services. In addition, recent disaster-related losses are incorporated to control for heterogeneity in exposure to production shocks, which may influence fertilizer application behavior and management decisions. Household income is expressed in logarithmic form to reduce heteroscedasticity and to facilitate interpretation of the estimated coefficients. The details and descriptive statistics for each variable are presented in Table 2.

Table 2. Variable definition and descriptive statistics for the 2024 household survey of wheat–maize farmers in five Chinese provinces.

Variables	Description	Mean	Std Dev.
Core variable			
Tillage practices	0 = CTS 1 = NTS 2 = DTS	0.8429	0.8535
Control Variables			
Age	Household head's actual age in 2023 (years)	61.2016	9.9671
Experience	Household head's experience in grain cultivation (years)	38.0288	13.0674
Household Income	Annual total household income in 2023, measured in CNY and log-transformed.	10.7780	1.1661
Fieldroad_access	Accessibility of field roads for traffic and agricultural machinery, as perceived by the household head (Likert scale, 1 = very inconvenient, 5 = very convenient)	4.0484	0.6724
Disaster_loss	Severity of agricultural losses caused by natural disasters over the past three years (Likert scale, 1 = not severe, 5 = very severe)	2.5203	1.3655
Irrig_access	Accessibility of irrigation for cultivated land, as perceived by the household head (Likert scale, 1 = very inconvenient, 5 = very convenient)	3.3432	0.9782
Land_fragmentation	Measured by the number of plots per hectare	0.0361	0.0269
Delivery	Village-level access to delivery services: whether there is a delivery station in the village (0/1)	0.5975	0.4959
Land_quality	Based on farmers' self-assessment of the quality of their cultivated land (Likert scale, 1 = very poor to 5 = very good)	3.3115	0.7173
Instrumental variables			
IV1	Whether the household head has participated in CT-related training programs (1/0)	0.1662	0.3724
IV2	Farmer's perception of whether CT contributes to environmental protection (Likert scale, 1 = strongly disagree, 5 = strongly agree)	3.7330	0.96130
Mechanism variables			
Fertilizer inputs	Fertilizer input intensity in wheat–maize production, measured in kg/ha	1988.0080	574.1379
Yield	Total yield of wheat–maize rotation in 2023 (kg/ha)	15,037.0650	2221.0470

Notes: The sample includes 1528 wheat–maize farmers from Shandong, Henan, Anhui, Shaanxi, and Shanxi provinces.

3.3.4. Mechanism Variables

To explore the channels through which different tillage practices affect FUE, two mechanism variables are introduced. The first mechanism variable is fertilizer input intensity, measured by the total amount of fertilizer applied in the wheat–maize rotation within a year. This variable captures potential changes in farmers' fertilizer application behavior induced by alternative tillage practices. The second mechanism variable is crop yield, measured by the total annual output of the wheat–maize rotation. This variable reflects the productivity response of crops to different tillage practices.

Table 3 reports the mean values of key variables across the three tillage types, together with the corresponding F-statistics testing the equality of group means. The results indicate pronounced differences in farmers' characteristics, production conditions, and efficiency outcomes across tillage practices. In particular, significant disparities are observed in farming experience, household income, infrastructure conditions, and training participation, suggesting that farmers adopting different tillage practices are not randomly distributed.

For instance, farmers adopting no-tillage exhibit higher household income levels and better access to field roads compared with those practicing conventional or deep tillage, while deep tillage adopters tend to experience greater disaster-related losses. Overall, the systematic differences documented suggest the presence of non-random selection into tillage practices. This reinforces the need to account for selection bias in the empirical analysis, motivating the use of the MESR framework in the subsequent estimations.

Table 3. Mean difference in key variables across CTS, NTS, and DTS among wheat–maize farmers in five Chinese provinces, 2024.

Variables	CTS	NTS	DTS	F-Statistics
Age	61.6978 (9.9322)	59.8280 (10.2289)	61.5846 (9.7136)	4.8106
Experience	39.2532 (13.446)	33.8492 (12.2078)	39.6308 (12.4418)	26.6731 *
Household Income	10.666 (1.1685)	11.0663 (1.1419)	10.7094 (1.1448)	15.8448
Fieldroad_access	4.0259 (0.7336)	4.2302 (0.7080)	3.9319 (0.4897)	21.5989 ***
Disaster_loss	2.5885 (1.4072)	1.9444 (1.2822)	2.8945 (1.2066)	55.2239 ***
Land_fragmentation	0.5878 (0.3629)	0.4922 (0.4178)	0.5093 (0.4394)	8.9714 ***
Irrig_access	3.2993 (1.0198)	3.6984 (0.6864)	3.4176 (1.0730)	20.9995 ***
Delivery	0.5856 (0.4959)	0.7540 (0.4493)	0.4857 (0.5003)	31.8136 *
Land_quality	3.2633 (0.6584)	3.4762 (0.7679)	3.2484 (0.7405)	13.5119 ***
IV1	0.0791 (0.2701)	0.2275 (0.4198)	0.2484 (0.4325)	36.8379 ***
IV2	3.6043 (1.0044)	3.9471 (0.8477)	3.7516 (0.9514)	15.9955 ***

Note: *** and * indicate that the estimates are significant at the 1% and 10% levels, respectively; numbers in parentheses are standard deviations.

4. Results

4.1. Calculation Results of Fertilizer Use Efficiency

Based on the estimation results of the SFA model, the likelihood ratio test strongly rejects the null hypothesis of “ $\sigma_u = 0$ ” at the 1% significance level. The ratio of the standard deviation of the technical inefficiency term to that of the random error term, denoted by λ , is estimated to be approximately 2.3235. This provides evidence of technical inefficiency among sampled grain farmers and indicates that the SFA specification is more appropriate than OLS for estimating farmers’ FUE.

Figure 1 presents the kernel density distributions of FUE for all farmers and by tillage practice. Overall, the average FUE in the sample is 0.5045, indicating a moderate level of FUE among wheat–maize producers in the study area. The distribution of farmers’ FUE exhibits substantial heterogeneity across tillage practices. The kernel density distribution of the SFA-derived FUE indicator shows two visible local peaks, suggesting that farmers are clustered in relatively low- and high-FUE groups. In particular, the distribution for NTS is markedly shifted to the right, with a large concentration of observations in the high-efficiency range, whereas DTS is concentrated more heavily in the lower-efficiency range. This pattern may reflect differences in the agronomic and operational characteristics of the two practices. NTS may improve the soil environment for fertilizer absorption by reducing soil disturbance and maintaining straw cover, while DTS is more dependent on soil compaction conditions, machinery quality, and standardized field operations. When these supporting conditions are insufficient, DTS may not translate its potential yield benefits into higher FUE. CTS occupies an intermediate position. These patterns indicate that different tillage choices are associated with substantial differences in the distribution of FUE, rather than merely differences in average efficiency levels.

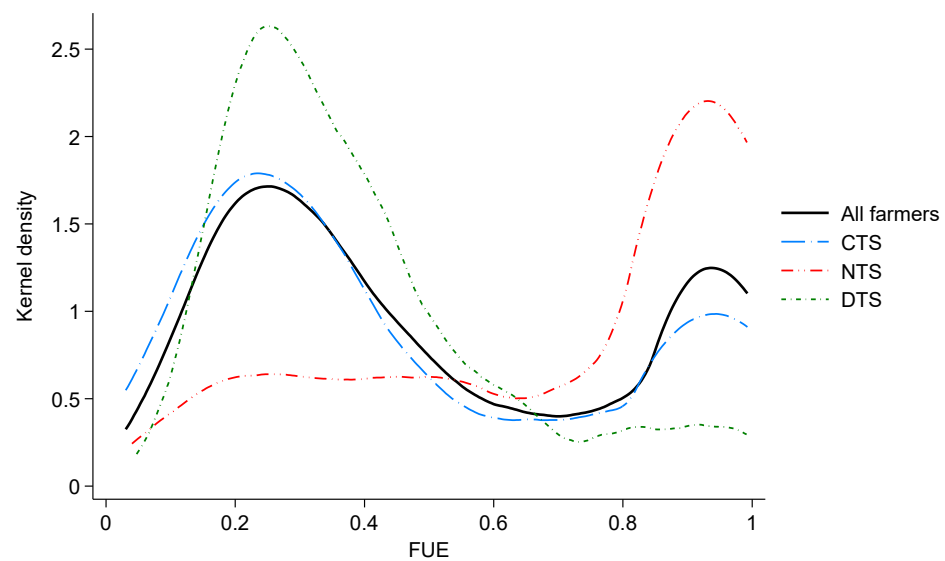


Figure 1. Kernel density distribution of FUE among wheat–maize farmers in five Chinese provinces by tillage practice, 2024.

4.2. Determinants of the Farmers' Tillage Choice

This section examines the determinants of farmers' tillage choices. Table 4 shows how farmers' characteristics, production conditions, and external support factors affect the probabilities of adopting CTS, NTS, and DTS. The results reveal substantial heterogeneity in tillage choices, indicating that farmers' adoption decisions are not random but are systematically associated with observable household and production characteristics. The corresponding MNL coefficient estimates are provided in Table A1 for reference.

Table 4. Determinants of the tillage choices among wheat–maize farmers in five Chinese provinces: marginal effects from the MNL model, 2024.

Variables	CTS	NTS	DTS
Age	−0.0039 * (0.0021)	0.0046 *** (0.0016)	−0.0007 (0.0019)
Experience	0.0041 ** (0.0016)	−0.0062 *** (0.0012)	0.0021 (0.0015)
Income	−0.0079 (0.012)	0.0168 (0.0102)	−0.0088 (0.0105)
Fieldroad_access	−0.0078 (0.0202)	0.0687 *** (0.0177)	−0.0609 *** (0.0160)
Disaster_loss	0.0088 (0.0095)	−0.0493 *** (0.0085)	0.0405 *** (0.0081)
Land_fragmentation	0.0891 ** (0.0449)	−0.0262 (0.0355)	−0.0629 (0.0454)
Irrig_access	−0.0470 *** (0.0136)	0.0456 *** (0.0120)	0.0013 (0.0128)
Delivery	0.0002 (0.0264)	0.0794 *** (0.0224)	−0.0796 *** (0.023)
Land_quality	0.0178 (0.0192)	0.0059 (0.0164)	−0.0237 (0.0180)
IV1	−0.2807 *** (0.0354)	0.1112 *** (0.0263)	0.1695 *** (0.0297)
IV2	−0.0488 *** (0.0131)	0.0327 *** (0.011)	0.0162 (0.0124)
Observations	1528	1528	1528

Note: ***, **, and * indicate that the estimates are significant at the 1%, 5%, and 10% levels, respectively; numbers in parentheses are standard errors.

Household-head characteristics are significantly associated with farmers' tillage choices. The marginal effects of age show that each additional year of the household head's age reduces the probability of adopting CTS by 0.39 percentage points and increases the probability of adopting NTS by 0.46 percentage points. This suggests that older farmers are less likely to remain with conventional rotary tillage and more likely to adopt no-tillage with straw return. By contrast, farming experience has the opposite effect. Each additional year of grain cultivation experience increases the probability of adopting CTS by 0.41 percentage points and decreases the probability of adopting NTS by 0.62 percentage points,

implying that more experienced farmers tend to rely on familiar tillage practices and are less inclined to shift to no-tillage systems.

Production conditions also significantly affect tillage choices. Better field-road access increases the probability of adopting NTS by 6.87 percentage points, indicating that favorable operating conditions and machinery accessibility are particularly important for the adoption of no-tillage practices. Irrigation access also matters. Better irrigation conditions reduce the probability of adopting CTS by 4.70 percentage points and increase the probability of adopting NTS by 4.56 percentage points, suggesting that no-tillage is more likely to be adopted under better water management conditions. A one-unit increase in the perceived severity of disaster-related losses reduces the probability of adopting NTS by 4.93 percentage points but raises the probability of adopting DTS by 4.05 percentage points. This suggests that farmers facing greater production risks may be less willing to adopt no-tillage and more likely to choose deep tillage instead.

Among the remaining variables, delivery access is particularly noteworthy. The presence of a delivery station in the village increases the probability of adopting NTS by 7.94 percentage points and decreases the probability of adopting DTS by 7.96 percentage points. This indicates that better village-level access to information and logistics services facilitates the adoption of no-tillage practices, while making deep tillage less likely. In addition, land fragmentation significantly increases the probability of adopting CTS, suggesting that fragmented land conditions may constrain farmers from shifting away from conventional rotary tillage.

The IVs also perform as expected. Participation in CT-related training significantly reduces the probability of adopting CTS by 28.07% and increases the probabilities of adopting NTS and DTS by 11.12% and 16.95%, respectively. This highlights the important role of training and extension services in promoting CT adoption. Similarly, stronger perceptions that CT contributes to environmental protection reduce the probability of adopting CTS by 4.88% and increase the probability of adopting NTS by 3.27%, suggesting that environmental awareness also encourages farmers to shift away from CTS.

4.3. Treatment Effect of Tillage Choice on Farmers' FUE

Based on the two-stage estimation of the MESR model, this paper further quantifies the treatment effects of alternative tillage practices on farmers' FUE. It should be clarified that the primary purpose of employing the MESR framework is to estimate the causal treatment effects of tillage choice on FUE, rather than to analyze the determinants of FUE. For brevity, the detailed second-stage results are reported in Appendix A (Table A2). Table 5 reports the ATT of tillage choice on farmers' FUE. By construction, the ATT measures the average effect of a given tillage practice on those farmers who actually adopted it, relative to the counterfactual outcome they would have obtained had they adopted CTS instead.

Table 5. Average treatment effects of NTS and DTS on FUE relative to CTS among wheat–maize farmers in five Chinese provinces, 2024.

Outcome Variables	Tillage Type	Mean Outcomes		
		Actual	Counterfactual	ATT
FUE	NTS vs. CTS	0.7128 (0.0070)	0.5537 (0.0057)	0.1591 *** (0.0045)
	DTS vs. CTS	0.3865 (0.0045)	0.4428 (0.0057)	−0.0562 *** (0.0040)

Note: *** indicate that the estimates are significant at the 1% levels; numbers in parentheses are standard errors.

The results show that, for farmers who actually adopted NTS, their observed FUE is significantly higher than the counterfactual FUE they would have achieved under CTS. The estimated ATT is 0.1591, indicating that no-tillage with straw return increases FUE by 0.1591 on average among its actual adopters. This suggests that, after accounting for both observable and unobservable selection bias, NTS can effectively improve FUE. This finding is broadly consistent with evidence that no-tillage can improve nutrient use efficiency and reduce fertilizer losses under suitable conditions.

By contrast, for farmers who actually adopted DTS, the estimated ATT is negative and statistically significant. Specifically, the observed FUE of DTS adopters is lower than the counterfactual FUE they would have obtained had they adopted CTS, with an ATT of -0.0562 . This means that, among actual DTS adopters, deep tillage with straw return reduces FUE relative to CTS. A possible explanation is that the efficiency effect of deep tillage is more conditional on production conditions and management quality and may not automatically translate into input-efficiency gains at the farm level.

Taken together, these results indicate that CT should not be treated as a homogeneous technology package. While NTS generates a significant positive effect on FUE for its actual adopters, DTS produces the opposite effect. This interpretation is also consistent with the broader literature showing that the effects of agricultural technologies are heterogeneous and depend on both the specific practice adopted and the conditions under which it is implemented.

4.4. Robustness Tests for the Effects of Tillage Choices on Farmers' FUE

This section evaluates the robustness of the conclusions through two checks. First, FUE is winsorized at the top and bottom 5% to reduce the influence of outliers. Second, the estimation strategy is altered by applying propensity score matching (PSM) using alternative matching algorithms. The results in Tables 6 and 7 show that, across all specifications, the estimated effects of NTS and DTS on FUE remain qualitatively unchanged. Therefore, these results confirm that the estimated positive effect of NTS and the negative effect of DTS on FUE are stable across alternative model specifications and sample treatments, reinforcing the credibility of the empirical findings.

Table 6. Results of the robustness test.

Outcome Variables	Tillage Type	Mean Outcomes		
		Actual	Counterfactual	ATT
FUE (winsorized)	NTS vs. CTS	0.7131 (0.0070)	0.5557 (0.0057)	0.1574 *** (0.0045)
	DTS vs. CTS	0.3870 (0.0045)	0.4453 (0.0056)	-0.0583 *** (0.0041)

Note: *** indicate that the estimates are significant at the 1% level; numbers in parentheses are standard errors.

Table 7. PSM robustness check for the effects of tillage choices on FUE among wheat–maize farmers in five Chinese provinces.

Variables	Matching Methods	Average Treatment Effect	t-Test Value
NTS	Kernel matching (bandwidth = 0.06)	0.1551 ** (0.0216)	7.1876
	K-nearest neighbor matching (k = 1)	0.1604 ** (0.0227)	7.0702
	Caliper matching (cal = 0.15)	0.1657 *** (0.0210)	7.8750
	Mean	0.1604	
DTS	Kernel matching (bandwidth = 0.06)	-0.0409 *** (0.0163)	-2.5072
	K-nearest neighbor matching (k = 1)	-0.0424 *** (0.0171)	-2.4738
	Caliper matching (cal = 0.15)	-0.0609 *** (0.0158)	-3.8463
	Mean	-0.0481	

Note: *** and ** indicate that the estimates are significant at the 1% and 5% levels, respectively; numbers in parentheses are standard errors.

4.5. Mechanism Analysis: Fertilizer-Input and Yield Channels

From an economic perspective, different tillage practices may affect FUE through adjustments on either the input side, the output side, or both. Having established that the main findings are robust across alternative specifications and estimation strategies, we next investigate the channels underlying these effects by examining fertilizer inputs and crop output responses. NTS and DTS are estimated separately relative to CTS; the regressions are reported in Table 8.

Table 8. Mechanism analysis among wheat–maize farmers in five Chinese provinces, 2024.

Variables	Fertilizer Input		Yield	
NTS	−278.8939 *** (39.9275)		1853.6010 *** (134.9042)	
DTS	−4.2501 (32.5241)		420.6075 *** (119.3414)	
Control variables	Controlled		Controlled	
Constant	2727.4330 *** (276.2464)	2783.5130 *** (249.2557)	11,209.5900 *** (933.3608)	11,013.7200 *** (914.6004)
Observations	1073	1150	1073	1150
R ²	0.1622	0.0782	0.2616	0.0783

Notes: Columns (1) and (3) are estimated using the CTS–NTS comparison subsample, while columns (2) and (4) are estimated using the CTS–DTS comparison subsample. Therefore, the number of observations differs across columns. *** indicate significance at the 1% level.

The results show that NTS affects FUE through both input reduction and output improvement. Specifically, relative to CTS, NTS significantly reduces fertilizer input intensity and significantly increases yield. This suggests that no-tillage with straw return not only helps farmers reduce fertilizer use, but also improves production performance at the same time. In other words, the positive effect of NTS on FUE appears to operate through a dual pathway: lowering fertilizer input redundancy on the one hand, and strengthening output realization on the other.

By contrast, the mechanism through which DTS affects FUE is different. The coefficient of DTS on fertilizer input is negative but statistically insignificant, indicating that deep tillage with straw return does not significantly reduce fertilizer use. However, DTS has a significantly positive effect on yield, suggesting that its role is mainly reflected in output improvement rather than input saving. This means that, although DTS may contribute to higher grain production, it does not appear to improve FUE by reducing fertilizer input at the farm level.

Taken together, the mechanism results indicate that different tillage practices influence FUE through distinct channels. For NTS, the improvement in FUE is jointly driven by lower fertilizer input and higher yield. For DTS, however, the mechanism is more limited and mainly operates through yield enhancement, with no clear evidence of fertilizer-saving effects. These findings further suggest that CT should not be treated as a uniform technology package, since different tillage practices may improve production performance through different pathways.

4.6. Threshold Effect Analysis of Tillage Choice on Farmers' FUE

To further examine whether the effects of tillage choice on farmers' FUE vary across farm-size conditions, this study conducts a threshold regression analysis. The threshold-effect tests are reported in Table 9, the estimated farm-size thresholds are presented in Table 10, and the threshold regression results are reported in Table 11. The threshold effect tests indicate that the effect of NTS on FUE is characterized by a single-threshold pattern, whereas the effect of DTS follows a double-threshold structure. These results suggest that the efficiency effects of tillage choice are nonlinear rather than constant across farm-size regimes.

Table 9. Tests for farm-size threshold effects of tillage choices on FUE among wheat–maize farmers in five Chinese provinces, 2024.

Variables	Threshold	F-Value	p-Value	Critical Value		
				1%	5%	10%
NTS	Single	11.529 **	0.010	11.659	9.32	6.505
	Double	2.539	0.177	18.676	8.191	4.943
DTS	Single	15.812 **	0.003	13.611	7.495	5.639
	Double	6.912 **	0.027	11.638	5.842	4.263

Note: ** indicate that the estimates are significant at the 5% level.

Table 10. Estimated farm-size thresholds for the effects of tillage choices on FUE among wheat–maize farmers in five Chinese provinces, 2024.

Variables	Threshold	Threshold Value	95% Confidence Interval
NTS	Th-11	4.5	[1.5, 9.0]
	Th-21	8	[3.2, 9.0]
DTS	Th-22	24	[12.0, 170.0]

Table 11. Farm-size threshold regression results for the effects of tillage choices on FUE among wheat–maize farmers in five Chinese provinces, 2024.

Variables	NTS	DTS
Small	0.0990 *** (0.0279)	−0.1020 *** (0.0189)
Medium		−0.0269 (0.0220)
Large	0.1880 *** (0.0222)	0.0957 * (0.0526)
Control variables	Controlled	Controlled
Constant	−0.0010 (0.1000)	0.0969 (0.1211)
Observations	1073	1150
R ²	0.2880	0.1980
F	38.92	23.39

Note: *** and * indicate that the estimates are significant at the 1% and 10% levels, respectively; numbers in parentheses are standard errors.

For NTS, the estimated threshold value is 4.5 mu, equivalent to 0.30 ha. The regression results show that NTS has a significantly positive effect on FUE in both regimes, but the positive effect becomes substantially stronger once cultivated land size exceeds 0.30 ha. This indicates that although no-tillage with straw return can improve FUE in general, larger-scale farmers are better able to translate this practice into efficiency gains.

For DTS, the estimated thresholds are 8 mu and 24 mu, equivalent to 0.53 ha and 1.60 ha, respectively. The regression results indicate that DTS is associated with a significantly negative effect on FUE when the cultivated land size is below 0.53 ha. When cultivated land size falls between 0.53 and 1.60 ha, the coefficient remains negative but loses statistical significance. A significantly positive effect emerges only when cultivated land size exceeds 1.60 ha. This pattern suggests that the FUE effect of DTS is highly conditional on operational scale and that its benefits can only be realized under relatively more favorable production conditions. Overall, the threshold regression results confirm that the effects of tillage choice on farmers' FUE are heterogeneous across farm-size regimes.

5. Discussion

The results show that conservation tillage practices have heterogeneous effects on farmers' FUE. Relative to CTS, NTS significantly improves FUE, whereas DTS reduces FUE on average [44]. The bimodal distribution of FUE further suggests that farmers are divided into

relatively low- and high-efficiency groups. This pattern should be interpreted as evidence of heterogeneous fertilizer-management capacity rather than as a purely China-specific phenomenon. Recent international evidence also shows that nutrient-use efficiency varies substantially across crops, regions, and production systems. A global assessment of major crops indicates that nitrogen and phosphorus use efficiencies remain highly context-dependent and differ by crop type and region [45]. Evidence from South Asia further shows that opportunities to improve nitrogen-use efficiency vary across sub-regions and farm-management conditions [46]. Farm-level evidence from the Eastern Indo-Gangetic Plains also suggests that fertilizer-use efficiency effects differ across farm-size groups and fertilizer-management conditions [47]. These studies are consistent with our finding that some farmers are able to combine tillage practices with efficient fertilizer management, whereas others remain constrained by land fragmentation, limited access to services, and weaker technical capacity.

The positive effect of NTS can be explained by both input-saving and output-enhancing mechanisms. The mechanism results show that NTS significantly reduces fertilizer input while increasing yield. This suggests that NTS improves FUE not only by reducing fertilizer redundancy but also by improving the production conditions under which fertilizer is converted into crop output. This finding is broadly consistent with previous evidence that conservation tillage can improve farm performance through output-enhancing and cost-saving pathways [48]. However, this study focuses specifically on fertilizer input rather than total production cost. Since chemical fertilizer is an important component of production inputs, the reduction in fertilizer input observed for NTS can be interpreted as a fertilizer-specific input-saving mechanism. By reducing soil disturbance and maintaining straw cover, NTS may improve soil moisture retention, reduce runoff and nutrient loss, and create better root-growth conditions.

By contrast, DTS can break compacted soil layers and improve root penetration, but its effect depends more strongly on soil conditions, machinery quality, and operation standards. Since DTS increases yield but does not significantly reduce fertilizer input, its yield-enhancing effect does not necessarily translate into higher FUE. This helps explain why DTS has a negative average effect on FUE, especially among small farms where machinery access and standardized field operations may be insufficient. This interpretation is consistent with international evidence showing that the performance of conservation agriculture is conditional on implementation quality and complementary production conditions. Studies from the Indo-Gangetic Plains show that conservation agriculture can improve productivity, soil carbon fractions, and resource-use performance, but these benefits depend on site-specific soil conditions, cropping systems, management duration, and farmer capacity [10]. Evidence from the western US Corn Belt also indicates that conservation tillage generates heterogeneous yield effects across climate, soil quality, and irrigation gradients [12]. More broadly, these findings are also consistent with studies showing that different CT technologies may generate markedly different efficiency effects and that some practices do not automatically improve technical efficiency [48]. They also accord with evidence that the impacts of conservation agriculture on farm performance and fertilizer use are heterogeneous and depend strongly on complementary conditions and farmers' resource endowments [15,43]. Therefore, our finding does not imply that DTS is universally inefficient. Rather, it suggests that machinery- and operation-intensive tillage practices may fail to improve FUE when applied on small and fragmented farms without adequate machinery services, soil-compaction diagnosis, and standardized field operations.

The mechanism results can also be interpreted through the perspectives of precision agriculture and global soil health. Precision agriculture emphasizes site-specific input management through soil testing, crop monitoring, remote sensing, variable-rate fertilization, and data-supported decision-making. Recent evidence suggests that precision

agriculture can optimize chemical fertilizer use, improve nutrient-use efficiency, and reduce environmental risks [18]. From this perspective, improving FUE requires not only reducing fertilizer input but also improving the match between fertilizer application, crop demand, and soil nutrient supply. The global soil health perspective further suggests that conservation agriculture should be understood not merely as reduced mechanical disturbance, but as a broader soil-management strategy involving residue retention, soil cover, improved soil structure, and enhanced biological activity. Recent evidence shows that conservation agriculture can improve soil health and sustain crop production under long-term warming conditions [19]. This perspective helps explain why NTS improves FUE through both reduced fertilizer input and increased yield, whereas DTS may fail to improve FUE when applied without soil-compaction diagnosis, appropriate machinery matching, and coordinated fertilizer management.

These findings can be better understood by comparing China's conservation tillage pathway with input-efficiency strategies in developed and emerging agricultural systems. In developed agricultural systems, input-efficiency improvement is often supported by larger farm size, stronger digital infrastructure, mature advisory services, and more standardized farm management. European evidence shows that sustainable soil management is increasingly connected with nutrient-loss reduction, fertilizer reduction, biodiversity protection, and climate-change mitigation [49]. Studies on European wheat systems further show that precision nitrogen management can improve fertilizer application by aligning nitrogen supply with crop demand and soil spatial heterogeneity [17]. In this context, fertilizer-efficiency gains are often achieved through the integration of conservation practices, precision nutrient management, and farm-level decision-support systems.

By contrast, in many emerging agricultural systems, input-efficiency strategies are more strongly constrained by small farm size, land fragmentation, limited access to specialized machinery, and uneven technical support. Evidence from India's Indo-Gangetic Plains shows that conservation agriculture, zero tillage, residue recycling, diversified cropping systems, and improved nutrient management can improve productivity, nutrient productivity, profitability, and environmental performance, but these effects depend on system design, local production conditions, and farmers' management capacity [11]. Evidence from Latin America also indicates that no-tillage systems need to be coordinated with cover crops, residue management, soil diagnosis, and nitrogen fertilization to improve FUE outcomes. In the Brazilian Cerrado, cover crops under no-tillage systems affect soil mineral nitrogen and maize nitrogen FUE, suggesting that soil conservation and fertilizer management need to be jointly considered [50].

Compared with these international pathways, China's wheat–maize production system has a distinct institutional feature: the central role of agricultural socialized services in overcoming smallholder constraints. Since many Chinese smallholders cannot efficiently purchase or operate specialized conservation tillage machinery individually, service-based adoption becomes central to improving FUE. Outsourced no-tillage seeding, straw-return operations, soil testing, formula fertilization, and field management training can reduce the fixed costs of technology adoption and improve the standardization of field operations. This interpretation is consistent with studies emphasizing the role of farm size in the adoption and performance of alternative tillage-related technologies, as larger farms usually have stronger resource capacity, better machinery access, and clearer economies of scale [51]. It is also related to evidence that agricultural technology adoption is facilitated by favorable production conditions and complementary support factors [15], while improved information access, training, knowledge, and environmental awareness can promote conservation-oriented agricultural practices [42,52]. Therefore, compared with developed markets that rely more heavily on precision agriculture and digital nutrient-management systems, and

compared with emerging markets where conservation agriculture often depends on farmers' own adoption capacity, China's model highlights the importance of service-supported conservation tillage for smallholder-based input-efficiency improvement.

This study has several limitations. First, the analysis is based on cross-sectional household survey data. Although the multinomial endogenous switching regression model is used to correct for self-selection bias, unobserved heterogeneity may still remain. Future research could use panel data or quasi-experimental designs to further identify the dynamic effects of conservation tillage on FUE. Second, FUE is estimated using a stochastic frontier analysis framework. This approach is useful for measuring farm-level fertilizer-oriented efficiency, but it cannot fully capture biophysical nutrient dynamics. Future studies could combine household survey data with soil testing, nitrogen-balance indicators, soil organic carbon, and field-level nutrient-loss measurements. Third, this study focuses on wheat–maize rotation systems in five Chinese provinces. Future studies could compare different regions, crop systems, and conservation tillage packages, with particular attention to the quality of agricultural socialized services, including machinery operation standards, service timing, straw-return quality, and the integration of tillage services with fertilizer-management guidance.

6. Conclusions and Policy Implications

6.1. Conclusions

This study is based on survey data from 1528 grain farmers to estimate farmers' FUE by the stochastic frontier translog production function model. It then employs the MESR model to examine the impact of tillage practices adoption on farmers' FUE and then explores the underlying mechanisms. Furthermore, the threshold regression model is applied to explore the threshold effect of the impact of tillage practices on farmers' FUE with respect to farm size. The main conclusions of this study are as follows.

First, farmers in the sample regions generally show technical inefficiency in grain production, indicating that there is room for improving FUE. The average FUE is 0.5045, indicating that with the current technical level and other input-output factors unchanged, there is the potential to reduce fertilizer input by 49.55%.

Second, the treatment effects of tillage choice on farmers' FUE are markedly heterogeneous. NTS significantly improves farmers' FUE, while DTS significantly reduces farmers' FUE. Under the counterfactual hypothesis, if farmers who actually adopt NTS were to switch to CTS, their FUE would decrease by 0.1591, equivalent to a decline of 28.73%. By contrast, if farmers who actually adopt DTS were to switch to CTS, their FUE would increase by 0.0562, equivalent to an increase of 12.69%.

Third, the mechanisms through which tillage practices affect FUE also differ. NTS improves FUE through both reduced fertilizer input and increased yield, indicating that its efficiency gains stem from both input saving and output enhancement. By contrast, DTS mainly operates through yield improvement, with no significant evidence that it reduces fertilizer input. This implies that higher productivity does not necessarily translate into higher FUE.

Fourth, the effects of tillage practices on farmers' FUE exhibit threshold heterogeneity across farm-size regimes. NTS exhibits a single-threshold effect, with its positive impact becoming stronger when cultivated land size exceeds 0.30 ha. DTS shows a double-threshold pattern: it reduces FUE when farm size is below 0.53 ha, has no significant effect when farm size is between 0.53 and 1.60 ha, and improves FUE only when farm size exceeds 1.60 ha. This indicates that farm size is an important conditioning factor shaping the FUE effects of tillage practices.

6.2. Policy Implications

Based on the above research results, the following policy implications can be derived:

First, local governments should strengthen technical guidance on fertilizer application, promote soil testing and formula fertilization, and improve field-level management training to reduce excessive fertilizer use under existing technological conditions. At the same time, improving farmers' access to production information and extension services is equally important for helping them move closer to the efficient production frontier.

Second, policies should promote the coordinated development of no-tillage, straw return, and scientific fertilizer management. This requires support for no-tillage seeding machinery, better access to straw treatment and return services, and closer integration between CT and precision fertilizer management. By contrast, the promotion of deep tillage with straw return should be more selective and better aligned with local soil and operational conditions. Where DTS is adopted, greater attention should be given to operation quality, machinery matching, and field management standards so that potential yield gains can be translated more effectively into input-use efficiency gains. In particular, DTS should not be promoted as a universal CT option, but should be conditionally adopted where soil compaction is present and standardized machinery services are available.

Third, farm size should be explicitly considered in the design of tillage promotion policies. The threshold regression results provide direct evidence for designing farm-size-based subsidy models and technical support packages. For farmers operating less than 4.5 mu, equivalent to 0.30 ha, policy support should prioritize low-threshold and service-based NTS adoption rather than individual machinery purchase subsidies. Specifically, local governments may provide service vouchers or operation-based subsidies for outsourced no-tillage seeding, straw-return operations, soil testing, and fertilizer management guidance. This would allow smallholders to benefit from NTS without bearing the fixed costs of specialized machinery. For smaller and more fragmented farmers, policy support should focus on technologies with lower scale requirements and stronger adaptability, such as NTS. By contrast, support for DTS should be directed mainly toward farmers with relatively larger and better-organized operations. More specifically, DTS should not be subsidized for farms below 8 mu, equivalent to 0.53 ha, because it significantly reduces FUE in this group. For farms between 8 and 24 mu, equivalent to 0.53–1.60 ha, DTS should be promoted only when soil compaction is verified and machinery service quality can be guaranteed. For farms above 24 mu, equivalent to 1.60 ha, DTS subsidies may be provided conditionally, together with technical standards for deep-tillage depth, straw incorporation, machinery matching, and fertilizer management. In this regard, measures such as land transfer, plot consolidation, and the development of moderate-scale farming can help create the conditions under which the efficiency gains of CT can be realized.

Fourth, agricultural socialized services should be strengthened to ease the operational constraints faced by smallholders. Since the effective implementation of alternative tillage practices often depends on machinery quality, field coordination, and standardized management, local governments should support specialized service providers in tillage, seeding, straw return, and machinery operation, while improving the availability of mechanized CT services at the village level. For small and fragmented farms, these services should be organized as integrated technical support packages that combine no-tillage seeding, straw-return services, soil testing, formula fertilization, and field management training. Such packages can reduce the indivisibility of machinery investment, improve operation quality, and help smallholders translate conservation tillage adoption into actual FUE gains. This service-based approach is particularly important for smallholders because it can lower the cost of accessing specialized conservation tillage equipment, improve the standardization of field operations, and provide complementary fertilizer-management

guidance. This would allow smallholders to adopt CT without bearing the full fixed costs of machinery purchase and operation.

Finally, CT policy should shift from simple technology diffusion toward efficiency-oriented promotion. The policy objective should not merely be to raise adoption rates, but to improve input-use efficiency and grain production performance under appropriate technical and operational conditions. Future policy design should therefore place greater emphasis on the match between tillage practices, farm size, and local production conditions, and evaluate CT not only by adoption outcomes, but also by its actual contribution to fertilizer-use efficiency and sustainable grain production. Accordingly, a differentiated policy framework should be established: NTS can be promoted more broadly through service-based support for smallholders and performance-based incentives for larger farms, whereas DTS should be promoted selectively according to farm size, soil conditions, and machinery-service capacity.

Author Contributions: Conceptualization, B.W. and X.B.; methodology, Y.W.; software, B.W.; validation, B.W. and Y.W.; formal analysis, B.W.; writing—original draft preparation, B.W.; writing—review and editing, B.W., Y.W. and X.B.; supervision, X.B.; project administration, X.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Ministry of Education of Humanities and Social Science Foundation (22YJA790001) and the Science and Technology Project of Yulin (2024-CXY-187).

Institutional Review Board Statement: Ethical review and approval were waived for this study due to according to article 32 of the Administrative Measures for Ethical Review of Life Science and Medical Research Involving Humans in China (https://www.gov.cn/zhengce/zhengceku/2023-02/28/content_5743658.htm, accessed on 11 May 2026). Article 32 states that studies using legally obtained public data, observational data generated without interfering with public behavior, or anonymized information data may be exempt from ethical review, provided that they do not cause harm to individuals and do not involve sensitive personal information or commercial interests. The study was based on an anonymous, non-interventional household questionnaire survey and did not involve any biomedical intervention, clinical trial, animal experiment, or collection of biological samples. No personally identifiable or sensitive personal information was collected, and the study posed no more than minimal risk to participants. Therefore, further ethics committee approval was not required for this study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

FUE	Fertilizer use efficiency
CT	Conservation tillage
CTS	Conventional rotary tillage with straw returning
NTS	No-tillage with straw returning
DTS	Deep tillage with straw returning
SFA	Stochastic frontier analysis
MESR	Multinomial endogenous switching regression
MNL	Multinomial logit
ATT	Average treatment effect on the treated
PSM	Propensity score matching
OLS	Ordinary least squares
IV	Instrumental variable

Appendix A

Table A1. Determinants of the tillage choices among CTS, NTS, and DTS.

Variables	NTS	DTS
Age	0.0317 *** (−0.0111)	0.0067 (−0.0109)
Experience	−0.0402 *** (−0.0083)	−0.0017 (−0.0088)
Income	0.1007 (−0.0685)	−0.0138 (−0.0581)
Fieldroad_access	0.3562 *** (−0.1248)	−0.2030 ** (−0.0928)
Disaster_loss	−0.2628 *** (−0.0594)	0.1265 *** (−0.0461)
Land_fragmentation	−0.3348 (−0.2365)	−0.4342 * (−0.2502)
Irrig_access	0.3332 *** (−0.0796)	0.1134 (−0.0705)
Delivery	0.3904 ** (−0.1536)	−0.2892 ** (−0.1314)
Land_quality	−0.0118 (−0.1098)	−0.1271 (−0.0993)
IV1	1.1962 *** (−0.1969)	1.2643 *** (−0.1857)
IV2	0.2736 *** (−0.0754)	0.1716 ** (−0.0693)
Constant	−5.4557 *** (−1.2096)	−0.5544 (−1.0219)
Observations	1528	1528

Notes: The estimates are based on the 2024 household survey of wheat–maize farmers in Shandong, Henan, Anhui, Shaanxi, and Shanxi provinces. ***, **, and * indicate that the estimates are significant at the 1%, 5%, and 10% levels, respectively; numbers in parentheses are standard errors.

Table A2. Second-stage outcome equations of the MESR model for farmers' FUE among wheat–maize farmers in five Chinese provinces, 2024.

Variables	CTS	NTS	DTS
Age	0.0060 * (0.0031)	−0.0051 (0.0039)	−0.0007 (0.0026)
Experience	−0.0056 (0.0036)	0.0073 * (0.0040)	0.0031 (0.0027)
Income	0.0233 * (0.0140)	0.0025 (0.0218)	0.0311 ** (0.0134)
Fieldroad_access	−0.0096 (0.0472)	−0.1107 * (0.0659)	−0.0597 * (0.0353)
Disaster_loss	−0.0509 (0.0309)	0.0736 * (0.0440)	0.0055 (0.0241)
Land_fragmentation	0.0008 (0.0389)	−0.1008 * (0.0598)	−0.1079 ** (0.0494)
Irrig_access	−0.0021 (0.0155)	−0.0787 * (0.0439)	−0.0204 (0.0156)
Delivery	0.1232 ** (0.0522)	0.0050 (0.0905)	−0.0517 (0.0426)
Land_quality	0.0579 ** (0.0263)	0.0645 * (0.0379)	−0.0016 (0.0200)
Ancillary			
rho1	0.1707 (0.6688)		−1.1062 *** (0.3166)
rho2	−0.2004 (0.6546)	1.1668 *** (0.3098)	
rho0		−0.4462 * (0.2584)	0.6177 *** (0.1864)
Constant	−0.0247 (0.3814)	1.6711 ** (0.7491)	0.1659 (0.2368)
Observations	695	378	455

Note: ***, **, and * indicate that the estimates are significant at the 1%, 5%, and 10% levels, respectively; numbers in parentheses are standard errors.

Appendix B. Household Questionnaire Used in the Survey

Appendix B.1. Identification of Tillage Practices

Before asking farmers about tillage practices, enumerators provided the following standardized definitions:

Conventional rotary tillage with straw returning (CTS): crop straw is returned to the field after harvest, and the soil is then rotary tilled before seeding.

No-tillage with straw returning (NTS): crop straw is retained or returned to the field, and direct seeding is conducted with minimal soil disturbance and without rotary tillage.

Deep tillage with straw returning (DTS): crop straw is returned to the field, and deep plowing or deep loosening is conducted to break compacted soil layers before or during field preparation.

Was crop straw returned to the field in your wheat–maize production during the 2023 production year?_(yes = 1, no = 0)

Was rotary tillage conducted before seeding?_(yes = 1, no = 0)

Was direct seeding without rotary tillage used?_(yes = 1, no = 0)

Was deep plowing or deep loosening conducted?_(yes = 1, no = 0)

What type of machinery was mainly used for tillage or seeding?

☐ Rotary tillage machinery ☐ No-tillage seeder ☐ Deep plowing/deep loosening machinery ☐ Other, please specify: ____

Appendix B.2. Input and Output Variables for Wheat–Maize Production

All questions in this module refer to the household's wheat–maize production in the 2023 production year. *Mu* is a traditional Chinese land-area unit. In this questionnaire, land area can be converted using the following relationship: 1 hectare (ha) = 15 mu.

Table A3. Questionnaire Module for Input and Output Variables in Wheat–Maize Production.

Item	Indicator	Wheat	Maize
Output	Farm size (mu)		
	Yield (kg/mu)		
	Price (CNY/kg)		
Sowing	Seed/seedling cost (CNY)		
Fertilization	Compound fertilizer (CNY; kg)		
	Nitrogen fertilizer (CNY; kg)		
	Phosphate fertilizer (CNY; kg)		
	Potassium fertilizer (CNY; kg)		
	Commercial organic fertilizer (CNY; kg)		
Pesticides	Insecticide (CNY)		
	Herbicide (CNY)		
Irrigation	Water and electricity cost (CNY)		
Plastic film	Total cost (CNY)		

Appendix B.3. Household, Farm, and Village-Level Characteristics

Age of household head in 2023: ____ years

Grain cultivation experience of household head: ____ years

Annual total household income in 2023: ____ CNY

Have you heard of conservation tillage before this survey?_(yes = 1, no = 0)

Have you participated in CT-related training programs?_(yes = 1, no = 0)

Do you think conservation tillage contributes to environmental protection?

1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree

Accessibility of field roads for traffic and agricultural machinery

Please evaluate the accessibility of field roads for traffic and agricultural machinery use.

1 = very inconvenient; 2 = inconvenient; 3 = moderate; 4 = convenient; 5 = very convenient

Accessibility of irrigation for cultivated land

Please evaluate the accessibility of irrigation for your cultivated land.

1 = very inconvenient; 2 = inconvenient; 3 = moderate; 4 = convenient; 5 = very convenient

Please evaluate the severity of agricultural production losses caused by natural disasters over the past three years.

1 = not severe; 2 = slightly severe; 3 = moderate; 4 = severe; 5 = very severe

Land fragmentation: Number of cultivated plots: ____; Total cultivated area: ____ mu

Self-assessed cultivated land quality

Please evaluate the overall quality of your cultivated land.

1 = very poor; 2 = poor; 3 = moderate; 4 = good; 5 = very good

Village-level delivery-service access: Is there a delivery station in the village?_(yes = 1, no = 0)

References

1. Falkendal, T.; Otto, C.; Schewe, J.; Jägermeyr, J.; Konar, M.; Kummu, M.; Watkins, B.; Puma, M.J. Grain Export Restrictions during COVID-19 Risk Food Insecurity in Many Low- and Middle-Income Countries. *Nat. Food* **2021**, *2*, 11–14. [\[CrossRef\]](#)
2. Du, Y.; Xu, Y.; Zhang, L.; Song, S. Can China's Food Production Capability Meet Her Peak Food Demand in the Future? *Int. Food Agribus. Manag. Rev.* **2020**, *23*, 1–17. [\[CrossRef\]](#)
3. Lal, R. Sustainable Intensification of China's Agroecosystems by Conservation Agriculture. *Int. Soil Water Conserv. Res.* **2018**, *6*, 1–12. [\[CrossRef\]](#)
4. Vos, R.; Glauber, J.; Hebebrand, C.; Rice, B. Global Shocks to Fertilizer Markets: Impacts on Prices, Demand and Farm Profitability. *Food Policy* **2025**, *133*, 102790. [\[CrossRef\]](#)
5. Jain, M.; Barrett, C.B.; Solomon, D.; Ghezzi-Kopel, K. Surveying the Evidence on Sustainable Intensification Strategies for Smallholder Agricultural Systems. *Annu. Rev. Environ. Resour.* **2023**, *48*, 347–369. [\[CrossRef\]](#)
6. Shi, X.; Liu, X.; Jing, J.; Zhang, Y.; Li, P.; Zong, Y.; Zhang, D.; Hao, X. Long-Term No Tillage Straw Mulching Increased Soil Water and Nitrogen Storage in Dryland Wheat on the Loess Plateau, but May Increase Dissolved Organic Nitrogen Leaching. *Field Crops Res.* **2025**, *322*, 109705. [\[CrossRef\]](#)
7. Song, F.; Liu, M.; Zhang, Z.; Qi, Z.; Li, T.; Du, S.; Li, A.; Liu, J. No-Tillage with Straw Mulching Increased Maize Yield and Nitrogen Fertilizer Recovery Rate in Northeast China. *Agric. Water Manag.* **2024**, *292*, 108687. [\[CrossRef\]](#)
8. Lu, X.; Li, Z.; Sun, Z.; Bu, Q. Straw Mulching Reduces Maize Yield, Water, and Nitrogen Use in Northeastern China. *Agron. J.* **2015**, *107*, 406–414. [\[CrossRef\]](#)
9. Ingraffia, R.; Lo Porto, A.; Ruisi, P.; Amato, G.; Giambalvo, D.; Frenda, A.S. Conventional Tillage versus No-Tillage: Nitrogen Use Efficiency Component Analysis of Contrasting Durum Wheat Genotypes Grown in a Mediterranean Environment. *Field Crops Res.* **2023**, *296*, 108904. [\[CrossRef\]](#)
10. Mishra, A.K.; Shinjo, H.; Jat, H.S.; Jat, M.L.; Kumar Jat, R.; Funakawa, S. Conservation Agriculture Enhances Crop Productivity and Soil Carbon Fractions in Indo-Gangetic Plains of India. *Front. Sustain. Food Syst.* **2024**, *8*, 1476292. [\[CrossRef\]](#)
11. Radheshyam; Jat, S.L.; Singh, A.K.; Jat, H.S.; Sharma, D.K.; Meena, M.C.; Gawdiya, S.; Kumar, A.; Kumar, R.; Singh, R.; et al. Conservation Agriculture Offers System Optimization for Legume Intensification: An on-Farm Study of Western Indo-Gangetic Plains. *Field Crops Res.* **2025**, *321*, 109677. [\[CrossRef\]](#)
12. Cambron, T.W.; Deines, J.M.; Lopez, B.; Patel, R.; Liang, S.-Z.; Lobell, D.B. Further Adoption of Conservation Tillage Can Increase Maize Yields in the Western US Corn Belt. *Environ. Res. Lett.* **2024**, *19*, 054040. [\[CrossRef\]](#)
13. He, P.; Zhang, J.; Li, W. The Role of Agricultural Green Production Technologies in Improving Low-Carbon Efficiency in China: Necessary but Not Effective. *J. Environ. Manag.* **2021**, *293*, 112837. [\[CrossRef\]](#)
14. Xie, J.; Wang, L.; Li, L.; Coulter, J.A.; Chai, Q.; Zhang, R.; Luo, Z.; Carberry, P.; Rao, K.P.C. Subsoiling Increases Grain Yield, Water Use Efficiency, and Economic Return of Maize under a Fully Mulched Ridge-Furrow System in a Semiarid Environment in China. *Soil Tillage Res.* **2020**, *199*, 104584. [\[CrossRef\]](#)
15. Ruzzante, S.; Labarta, R.; Bilton, A. Adoption of Agricultural Technology in the Developing World: A Meta-Analysis of the Empirical Literature. *World Dev.* **2021**, *146*, 105599. [\[CrossRef\]](#)
16. Liu, T.; Bruins, R.J.F.; Heberling, M.T. Factors Influencing Farmers' Adoption of Best Management Practices: A Review and Synthesis. *Sustainability* **2018**, *10*, 432. [\[CrossRef\]](#)
17. Fabbri, C.; Delgado, A.; Guerrini, L.; Napoli, M. Precision Nitrogen Fertilization Strategies for Durum Wheat: A Sustainability Evaluation of NNI and NDVI Map-Based Approaches. *Eur. J. Agron.* **2025**, *164*, 127502. [\[CrossRef\]](#)
18. Cai, B.; Shi, F.; Geremew, B.A.; Addis, A.K.; Abate, M.C.; Dessie, W.; Bayu, T. Precision Agriculture Techniques for Optimizing Chemical Fertilizer Use and Environmental Sustainability: A Systematic Review. *Front. Agron.* **2025**, *7*, 1665444. [\[CrossRef\]](#)
19. Teng, J.; Hou, R.; Dungait, J.A.J.; Zhou, G.; Kuzyakov, Y.; Zhang, J.; Tian, J.; Cui, Z.; Zhang, F.; Delgado-Baquerizo, M. Conservation Agriculture Improves Soil Health and Sustains Crop Yields after Long-Term Warming. *Nat. Commun.* **2024**, *15*, 8785. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Wu, H.; Ran, L.; Wang, J.; Yan, S.; Xue, Y.; Xia, F.; Shi, H.; Wei, W.; Zhang, Y.; Zheng, S. Tillage Effects on Maize Yield, N Use Efficiency and GHG Emissions under Parallel N Application in Northwest China. *Field Crops Res.* **2025**, *322*, 109735. [\[CrossRef\]](#)
21. Liu, D.; Tian, B.; Zhang, M.; Jiang, L.; Li, C.; Qin, X.; Ma, J. Meta-Analysis of the Effects of Different Tillage Methods on Wheat Yields under Various Conditions in China. *Soil Tillage Res.* **2025**, *248*, 106449. [\[CrossRef\]](#)
22. Yang, H.; Li, J.; Wu, G.; Huang, X.; Fan, G. Maize Straw Mulching with No-Tillage Increases Fertile Spike and Grain Yield of Dryland Wheat by Regulating Root-Soil Interaction and Nitrogen Nutrition. *Soil Tillage Res.* **2023**, *228*, 105652. [\[CrossRef\]](#)

23. Iqbal, A.; Khan, A.; Green, S.J.; Ali, I.; He, L.; Zeeshan, M.; Luo, Y.; Wu, X.; Wei, S.; Jiang, L. Long-Term Straw Mulching in a No-till Field Improves Soil Functionality and Rice Yield by Increasing Soil Enzymatic Activity and Chemical Properties in Paddy Soils. *J. Plant Nutr. Soil Sci.* **2021**, *184*, 622–634. [\[CrossRef\]](#)
24. Mkomwa, S.; Kaumbutho, P.; Makungu, P. Farm Machinery for Conservation Agriculture. In *Conservation Agriculture*; Farooq, M., Siddique, K.H.M., Eds.; Springer International Publishing: Cham, Switzerland, 2015; pp. 109–131. ISBN 978-3-319-11620-4.
25. Jug, D.; Đurđević, B.; Birkás, M.; Brozović, B.; Lipiec, J.; Vukadinović, V.; Jug, I. Effect of Conservation Tillage on Crop Productivity and Nitrogen Use Efficiency. *Soil Tillage Res.* **2019**, *194*, 104327. [\[CrossRef\]](#)
26. Rogers, S.; Wilmsen, B.; Han, X.; Wang, Z.J.-H.; Duan, Y.; He, J.; Li, J.; Lin, W.; Wong, C. Scaling up Agriculture? The Dynamics of Land Transfer in Inland China. *World Dev.* **2021**, *146*, 105563. [\[CrossRef\]](#)
27. Wang, X.; Song, Y.; Huang, W. The Effects of Agricultural Machinery Services and Land Fragmentation on Farmers' Straw Returning Behavior. *Agribusiness* **2026**, *42*, 104–126. [\[CrossRef\]](#)
28. Hu, Y.; Li, B.; Zhang, Z.; Wang, J. Farm Size and Agricultural Technology Progress: Evidence from China. *J. Rural Stud.* **2022**, *93*, 417–429. [\[CrossRef\]](#)
29. Aryal, J.P.; Rahut, D.B.; Thapa, G.; Simtowe, F. Mechanisation of Small-Scale Farms in South Asia: Empirical Evidence Derived from Farm Households Survey. *Technol. Soc.* **2021**, *65*, 101591. [\[CrossRef\]](#)
30. Amankwah, A.; Gwatidzo, T. Food Security and Poverty Reduction Effects of Agricultural Technologies Adoption – a Multinomial Endogenous Switching Regression Application in Rural Zimbabwe. *Food Policy* **2024**, *125*, 102629. [\[CrossRef\]](#)
31. Ma, W.; Zheng, H.; Boansi, D.; Horlu, G.S.A.K.; Owusu, V. Types of Employment and Well-Being of Rural Residents: A Multinomial Endogenous Switching Regression Application. *Econ. Model.* **2025**, *147*, 107047. [\[CrossRef\]](#)
32. Zheng, H.; Ma, W.; Rahut, D.B. Fuel Choices for Cooking and Heating and Gender Empowerment: Implications for Promoting Gender Equality and Sustainable Rural Development. *Energy Econ.* **2025**, *141*, 108104. [\[CrossRef\]](#)
33. Koppenberg, M.; Mishra, A.K.; Hirsch, S. Food Aid and Violent Conflict: A Review and Empiricist's Companion. *Food Policy* **2023**, *121*, 102542. [\[CrossRef\]](#)
34. Tran, N.L.D.; Rañola, R.F., Jr.; Ole Sander, B.; Reiner, W.; Nguyen, D.T.; Nong, N.K.N. Determinants of Adoption of Climate-Smart Agriculture Technologies in Rice Production in Vietnam. *Int. J. Clim. Change Strateg. Manag.* **2020**, *12*, 238–256. [\[CrossRef\]](#)
35. Kule, E.K.; Obia, A.; Agole, D.; Okello, D.M.; Odongo, W. Farmer Perceptions and Their Implications for Adoption of Sustainable Agricultural Intensification Practices. *Discov. Sustain.* **2025**, *6*, 210. [\[CrossRef\]](#)
36. Luh, Y.-H.; Tsai, M.-H.; Chang, Y.-C. Actions Speak Louder than Words: Adoption of Sustainable Farming Practices Based on an Integrated Model. *J. Clean. Prod.* **2023**, *416*, 137856. [\[CrossRef\]](#)
37. Bai, X.; Wang, Y.; Huo, X.; Salim, R.; Bloch, H.; Zhang, H. Assessing Fertilizer Use Efficiency and Its Determinants for Apple Production in China. *Ecol. Indic.* **2019**, *104*, 268–278. [\[CrossRef\]](#)
38. Battese, G.E.; Coelli, T.J. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empir. Econ.* **1995**, *20*, 325–332. [\[CrossRef\]](#)
39. Reinhard, S.; Lovell, C.A.K.; Thijssen, G. Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms. *Am. J. Agric. Econ.* **1999**, *81*, 44–60. [\[CrossRef\]](#)
40. Ye, F.; Sun, S.; Razzaq, A.; Zhang, Q. Harvesting Environmental Sustainability—The Fertilizer Use Efficiency Gains of China's High-Standard Farmland Initiative. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 846. [\[CrossRef\]](#)
41. Yang, Y.; Qi, C.; Gu, Y.; Fang, G. Use Efficiency, Reduction Potential, and Effects of Fertilizers on Carbon Emissions in China's Major Citrus Regions. *Agriculture* **2024**, *14*, 1971. [\[CrossRef\]](#)
42. Maharjan, K.L.; Singh, M.; Gonzalvo, C.M. Drivers of Environmental Conservation Agriculture and Women Farmer Empowerment in Namobuddha Municipality, Nepal. *J. Agric. Food Res.* **2023**, *13*, 100631. [\[CrossRef\]](#)
43. Adam, B.; Abdulai, A. Heterogeneity in the Impact of Conservation Agriculture Practices on Farm Performance and Inorganic Fertilizer Use in Ghana. *J. Agric. Resour. Econ.* **2022**, *47*, 225–245. [\[CrossRef\]](#)
44. Yan, F.; Zhou, W.; Sun, Y.; Guo, C.; Xiang, K.; Li, N.; Yang, Z.; Wu, Y.; Zhang, Q.; Sun, Y.; et al. No-Tillage with Straw Mulching Promotes the Utilization of Soil Nitrogen by Rice under Wheat–Rice and Oilseed Rape–Rice Cropping Systems. *Front. Plant Sci.* **2023**, *14*, 1170739. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Liu, J.; Wang, H.; Penuelas, J.; Mou, J.; Delgado-Baquerizo, M.; Sardans, J.; Coello, F.; Quan, Z.; Qiu, T.; Li, Y.; et al. Global-Scale Prevalence of Low Nutrient Use Efficiency across Major Crops. *Nat. Commun.* **2025**, *16*, 11036. [\[CrossRef\]](#)
46. Coggins, S.; McDonald, A.J.; Silva, J.V.; Urfels, A.; Nayak, H.S.; Sherpa, S.R.; Jat, M.L.; Jat, H.S.; Krupnik, T.; Kumar, V.; et al. Data-Driven Strategies to Improve Nitrogen Use Efficiency of Rice Farming in South Asia. *Nat. Sustain.* **2025**, *8*, 22–33. [\[CrossRef\]](#)
47. Paudel, G.P.; Chamberlin, J.; Grote, U.; Nguyen, T.T. Sustainable Intensification of Wheat through Early Sowing: Insights from the Eastern Indo-Gangetic Plains. *Environ. Dev. Sustain.* **2025**. [\[CrossRef\]](#)
48. Teng, C.; Lyu, K.; Zhu, M.; Zhang, C. Impact of Conservation Tillage Technology Application on Farmers' Technical Efficiency: Evidence from China. *Agriculture* **2023**, *13*, 1147. [\[CrossRef\]](#)

49. Keesstra, S.D.; Chenu, C.; Munkholm, L.J.; Cornu, S.; Kuikman, P.J.; Thorsøe, M.H.; Besse-Lototskaya, A.; Visser, S.M. European Agricultural Soil Management: Towards Climate-Smart and Sustainability, Knowledge Needs and Research Approaches. *Eur. J. Soil Sci.* **2024**, *75*, e13437. [[CrossRef](#)]
50. Carvalho, A.M.d.; Ramos, M.L.G.; da Silva, V.G.; de Sousa, T.R.; Malaquias, J.V.; Ribeiro, F.P.; de Oliveira, A.D.; Marchão, R.L.; da Fonseca, A.C.P.; Dantas, R.d.A. Cover Crops Affect Soil Mineral Nitrogen and N Fertilizer Use Efficiency of Maize No-Tillage System in the Brazilian Cerrado. *Land* **2024**, *13*, 693. [[CrossRef](#)]
51. Brown, W.M.; Ferguson, S.M.; Viju-Miljusevic, C. Farm Size, Technology Adoption and Agricultural Trade Reform: Evidence from Canada. *J. Agric. Econ.* **2020**, *71*, 676–697. [[CrossRef](#)]
52. Ma, W.; Wang, X. Internet Use, Sustainable Agricultural Practices and Rural Incomes: Evidence from China. *Aust. J. Agric. Resour. Econ.* **2020**, *64*, 1087–1112. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.