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The impact of agricultural farmland scale management on land yield: a perspective based on the adoption of agricultural machinery in different production links

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Introduction: The existing research on the relationship between farm size and land yield has been controversial because it fails to clarify the differences in factor substitution and technological progress across machinery technologies used in different production links.

Methods: Based on micro-level farmer data from the 2020 China Rural Revitalization Survey (CRRS) database, this paper uses a stochastic Frontier model (SFM) to systematically analyze the impact of machinery technology at different production links on the relationship between the farm size and land yield of staple crops, revealing the significant role of technological progress in promoting the development of farmland scale management.

Conclusion: The research results indicate that before incorporating machinery technology variables, there is an “inverse relationship” between the farm size and land yield for all three crops, meaning that the larger the farm size, the lower land yield. After incorporating machinery technology variables, the “inverse relationship” was alleviated for wheat and rice, while it was reversed for corn. After considering technical efficiency losses and adjusting the coefficients of farm size, the regression results show no significant changes. Compared to power-intensive machinery technologies, control-intensive machinery technologies have a more significant role in improving this relationship. Further analysis indicates that as farm size increases, the total factor productivity index at the farmer level for the three crops shows an upward trend, with the adoption of control-intensive machinery technologies playing an important role. Therefore, moderate-scale farming is an effective means to ensure food security, and its development process should place greater emphasis on the development and application of control-intensive machinery technologies such as spraying and fertilization.

KEYWORDS

farm size, land yield, machinery technology, power-intensive, control-intensive

1 Introduction

“Food is the paramount necessity of the people, and when grain is abundant, the world is peaceful.” Ensuring food security has always been the top priority for both national governance and people’s livelihoods. The primary task for building a strong agricultural nation is to ensure the stable and safe supply of food and important agricultural products, with a focus on stabilizing acreage and increasing yield per unit area. With the continued urbanization in China and the continuous migration of agricultural labor to towns and cities, the farmland scale management in agriculture has rapidly developed, effectively improving agricultural labor productivity and increasing income levels from grain production. However, the relationship between farm size and land yield has been controversial due to economies or diseconomies of scale. The study on the relationship between farm size and land yield can be traced back to the 1920s. Russian scholar [Chaianov \(1986\)](#) found that, under the same technological level, crop yields per unit area tend to decrease as the farm size expands, which is the classic “inverse relationship” ([Sen, 1962; Barrett, 2010](#)). This phenomenon has been repeatedly confirmed by numerous empirical studies ([Berry et al., 1980; Collier, 1983; Carter, 1984; Heltberg, 1998; Alvarez and Arias, 2003; Yan, 2019](#)). This phenomenon occurs because traditional smallholder farmers, relying on intensive labor input, achieve higher yields per unit of land. However, as farm size expands, there is insufficient supervision of hired labor, which leads to a decline in land yield.

With the continuous innovation of agricultural technology, traditional production models have gradually been disrupted. Since the 1940s, the Green Revolution aimed at increasing grain yields and addressing food shortages has been widely implemented in developing countries. By promoting biotechnology and modern agricultural techniques, it has significantly advanced agricultural development. Since the 1960s, China has drawn on international experience by introducing improved grain crop varieties, promoting the use of chemical fertilizers and pesticides, and popularizing agricultural machinery, thereby substantially increasing grain yields ([Foster and Rosenzweig, 2022](#)). As this process deepened, large-scale farmers, leveraging their greater resource endowments and stronger learning capabilities, not only achieved widespread substitution of machinery for labor but also tended to adopt more advanced biotechnologies. In contrast, smallholder farmers often prefer traditional production technologies that fully utilize their labor advantages, leading to a divergence in technology adoption paths between them and large-scale farmers ([Gong et al., 2020](#)). However, China’s current grain production has not yet achieved complete substitution of machinery for labor, as certain mechanized processes still require a significant amount of labor input. This inevitably subjects farmland scale management to labor shortage constraints. More critically, the expansion of farm size has increased the complexity of field management, particularly in areas such as fertilization and spraying, further exacerbating labor shortages. This undermines the yield potential of biotechnologies and may ultimately lead to extensive management practices by large-scale farmers ([Han, 2023](#)). If the technological advantages of large-scale farmers cannot compensate for the disadvantages of labor shortages, the “inverse relationship” between farm size and land yield is likely to persist. This could pose a threat to China’s future food security

goals and hinder the sustainable development of farmland scale management. This raises the core questions: What is the relationship between farm size and land yield in China’s grain production? How can the compatibility between farmland scale management and high yields be achieved?

Existing studies generally agree that the substitution of machinery for labor in grain production not only alleviates the labor constraints and supervision costs faced by farmland scale management but also reduces the willingness of smallholder farmers to engage in “intensive farming.” This effectively mitigates the “inverse relationship” between farm size and land yield ([Assuncao and Ghatak, 2003; Otsuka et al., 2016](#)). Some studies have found that farmers who substitute labor with machinery for farmland scale management have achieved land yield levels that reach or even exceed those of smallholders ([Fan and Zhou, 2014; Wang et al., 2015; Huang and Ding, 2016; Bevis and Barrett, 2020](#)). This phenomenon has been widely observed in developed countries ([Alvarez and Arias, 2003; Sheng and Chancellor, 2019; Key, 2019](#)). Some also studies have also found that the relationship between farm size and land yield is not a simple linear one; it may follow a “U-shaped” or “inverted U-shaped” pattern. Scholars who support the “U-shaped” view argue that the degree of labor substitution by machinery increases as farm size expands, which results in the lowest land yield for medium-size farms that are most dependent on hired labor ([Muyanga and Jayne, 2019; Foster and Rosenzweig, 2022](#)). On the other hand, research supporting the “inverted U-shaped” view suggests that farmers with strong management abilities are more likely to expand their land area by transferring more land, achieving the highest land yield at the medium-size stage. However, as the farm size continues to grow, they may face diminishing returns due to insufficient management, leading to a decline in land yield ([Yan et al., 2016; Zheng et al., 2024](#)).

One of the controversies in existing research lies in the failure to clarify the role of agricultural machinery technology in different production links in the relationship between farm size and land yield. Neoclassical economics distinguishes between factor substitution and technological progress: the former refers to changes in the factor input structure, represented by the movement of the production point along the isoquant curve, while the latter refers to the increase in output per unit of input, represented by the movement of the isoquant curve itself ([Ellis, 1993](#)). The development of agricultural machinery technology typically involves both factor substitution and technological progress occurring simultaneously. Existing research often treats agricultural technological progress as an exogenous variable, focusing on the impact of farm size expansion on the structure of factor inputs. However, expanding the farm size not only affects the proportion of factor inputs, but it may also have an endogenous relationship with agricultural technological progress, as expanding the farm size may encourage farmers to adopt more advanced machinery technology. If factor substitution alone cannot fully explain the changes in the relationship between farm size and land yield, then it is necessary to further consider the role of technological progress. In food production, the adoption of agricultural machinery technology covers various links such as cultivating, seeding, harvesting, spraying, fertilizing, and irrigation. The emphasis of machinery technology in each production link on factor substitution and technological

advancement varies, and this emphasis changes with farm size. As a result, the impact of technological adoption in different links on the relationship between farm size and land yield may also differ. Therefore, to scientifically understand the relationship between farm size and land yield, it is necessary to comprehensively consider the effects of factor substitution and technological adoption (Sheng et al., 2015; Ayaz and Mughal, 2024).

This study uses micro-level data from the China Rural Revitalization Survey (CRRS) initiated by the Institute of Rural Development, Chinese Academy of Social Sciences, to systematically analyze the relationship between farm size, land yield, and agricultural machinery technology. Based on the existing literature (Gautam and Ahmed, 2019; Foster and Rosenzweig, 2022), the innovations of this paper are as follows: At the theoretical level, existing research primarily focuses on the substitution effect of machinery technology on labor. Building on this, our study further identifies the role of machinery technology in promoting agricultural technological progress and reveals how technological progress facilitates farmland scale management. This research not only deepens the understanding of the functions of machinery technology but also provides new perspectives and insights for the theoretical exploration of farmland scale management. At the practical level, the study selects wheat, rice, and maize as the research subjects and analyzes in-depth the differentiated impact of agricultural machinery technology on the relationship between farm size and land yield for different crops, offering valuable references for the development of farmland scale management in China.

This study is structured as follows. Section 2 shows the theoretical of the impact of machinery technology on the relationship between farm size and land yield. Section 3 introduces the model specification. Section 4 presents the data sources and the results of the empirical analysis. Section 5 analyzes the impact of machinery technologies in different production links on technological progress. Section 6 discusses the contribution and limitations of the study. Section 7 draws conclusions and lay out the policy implications.

2 Theoretical analysis

Farmers expand their farm size with the goal of increasing operational profitability, a process that is typically accompanied by adjustments in factor structure and changes in production technology. Factor structure adjustment includes both the changes in economies of scale brought about by proportional increases in factors and the changes in input intensity of land factors determined by factor prices. Meanwhile, changes in production technology affect the output level per unit of input. Therefore, the impact of farm size on land yield depends on the combined effect of these two factors.

2.1 The impact of farm size on factor structure adjustment

Returns to Scale refer to the changes in output resulting from proportional changes in inputs under a given level of technology.

These changes can manifest as increasing returns to scale, decreasing returns to scale, or constant returns to scale (Hu and Gao, 2000). In theory, achieving increasing returns to scale in agricultural production requires two conditions: firstly, in the process of proportional factor aggregation under the given level of technology, the efficiency of factor allocation is improved, which promotes specialization and division of labor; secondly, each producer exerts the same level of effort in different combinations of production factors (Xu et al., 2011; Sheng et al., 2015). However, unlike in industrial sectors, the indivisibility of production factors in agriculture is less pronounced, leading to less significant effects from proportional increases in production factors. Moreover, agriculture is an industry where effective supervision of labor during the production process is lacking, which means that even if proportional increases in production factors have the potential to achieve increasing returns to scale, they are often offset by insufficient labor supervision (Lucas, 1978; Adamopoulos and Restuccia, 2014). As a result, proportional increases in production factors in agriculture often lead to diminishing returns to scale.

Farmers, aiming to maximize their operational profitability, decide the intensity of input for each unit of land based on the market prices of production factors (Li et al., 2010; Barrett, 2010; Yu et al., 2022). At present, agricultural production in China cannot achieve complete substitution of labor by machinery and still requires a certain amount of labor input, including both family labor and hired labor. When the farm size is small, family labor can be managed more precisely, and the labor input per unit of land is higher. As the farm size increases, the family labor force is unable to maintain the same level of management precision, while hired labor faces high supervision costs. This results in an increase in the relative “price” of labor (Feder, 1985; Carletto et al., 2013; Valtiala et al., 2023). To ensure operational profitability, rational farmers would choose to reduce labor input per unit of land, but the reduction in labor input cannot be fully compensated by agricultural machinery. Meanwhile, the decline in management precision due to labor shortages reduces the efficiency of capital inputs such as fertilizers and pesticides, leading to a decrease in capital input intensity per unit of land (Eswaran and Kotwal, 1986; Abay et al., 2019). This suggests that, with technology remaining unchanged, an increase in farm size will lead to a decrease in the intensity of labor and capital inputs per unit of land, thereby reducing land yield.

2.2 The impact of farm size on agricultural technological progress

In agricultural production, technological progress includes advancements in physical technologies such as machinery, biological, and chemical technologies, as well as improvements in production and management efficiency. Relative to other technologies, biological and chemical technologies are more easily subdivided to fit different farm sizes and are generally considered size-neutral. Although machinery technologies can also be subdivided based on power size to suit different farm sizes, high-horsepower machinery tends to carry more advanced production technologies (Gautam and Ahmed, 2019; Key, 2019; Helfand and

Taylor, 2021). In other words, the farm size determines the level of machinery, and the level of machinery directly influences production technology.

According to the varying demands for power and management skills, machinery technologies can be divided into power-intensive and control-intensive components (Pingali, 2007). Power-intensive components, such as cultivation, harvesting, and irrigation, have a high degree of standardization and significant power requirements. Machinery technologies in these areas primarily focus on replacing manual labor, particularly in heavy operations, where they can significantly reduce labor costs. In contrast, control-intensive components, such as seeding, fertilizing, and spraying, require higher levels of specialized skills. In these areas, machinery technologies are more focused on precision management, improving the uniformity and health of crop growth, thereby enhancing both yield and quality, and maximizing the productive potential of the land.

The aging and feminization of the agricultural labor force have reduced family labor quality, prompting smallholder farmers to demand machinery for labor replacement. Their production methods usually combine family labor with small-size agricultural machinery, which mainly compensates for labor shortages (Zheng and Xu, 2017; Zhang et al., 2016). At this stage, various types of machinery technologies primarily serve to replace labor. As the farm size expands, the complexity and management difficulty of food production also increase, which not only raises the demand for labor-replacing machinery but also imposes more refined requirements for management and technology. To counter potential marginal output losses brought about by scaling up, large-scale farmers typically replace medium and small machinery with larger machinery (Ji and Zhong, 2013; Omotilewa et al., 2021). At this point, machinery technology begins to show differences across various links.

Power-intensive tasks (such as cultivation, harvesting, and irrigation) are characterized by a high degree of standardization and significant power requirements. Machinery technologies in these links primarily focus on replacing manual labor, particularly in heavy-duty operations, leading to substantial labor savings. For example, large farms in the Midwestern United States use high-horsepower tractors for cultivation and seeding, where a single tractor can replace the labor of dozens of people, increasing cultivation efficiency by more than threefold. In contrast, control-intensive links (such as seeding, fertilization, and spraying) involve the application of biotechnology. These links not only require a certain level of power support but also demand higher professional skills, placing greater demands on machinery technologies. This includes precise crop management and improving the uniformity and health of crop growth, thereby maximizing the production potential of the land (Mandal, 2002; Zhang and Yi, 2015). For instance, in northeastern China, large-scale farmers use precision fertilizer applicators to precisely control the amount of fertilizer based on soil nutrient data and crop needs. This technology not only reduces fertilizer usage but also improves fertilizer efficiency, increasing corn yield by 10%–15%. Additionally, rice farmers in Jiangsu Province use plant protection drones for pesticide spraying, achieving precision operations through GPS positioning and sensor technology. Data shows that pesticide usage has decreased by 20%,

pest control effectiveness has significantly improved, and rice yield has increased by 5%–8%.

2.3 Economic analysis of the impact of farm size on land yield

From both the perspective of returns to scale of factors and the intensity of factor input per unit of land, expanding the farm size by farmers leads to a decrease in land yield. In order to compensate for this yield loss and increase operational profits, farmers choose to adopt new machinery technologies to improve the output level per unit of input. As shown in Figure 1 assuming that farmers only use land (T) and labor (L) as production factors (with land and capital being similar), Q represents the optimal production Frontier achievable by the two factors on a unit of land. T_L denotes the farm size of large-scale farmers, and T_S represents the farm size of small farmers. L_L refers to the labor input of large-scale farmers, and L_S refers to the labor input of smallholder farmers. In an ideal state, where the technology level is the same, returns to scale are constant, and there is perfect market competition, the production capabilities of farmers with different farm sizes should be indistinguishable, all lying on the same optimal Frontier. In reality, large-scale farmers face diminishing returns to scale of factors and marginal output losses caused by imperfect market competition. Compared to smallholder farmers (B), their actual production capacity (A) is farther from the optimal production Frontier. However, there are differences in machinery technology across different links: in power-intensive links such as cultivation, harvesting, and irrigation, machinery primarily plays a role in factor substitution, improving farm efficiency, which moves the production point from A to A' . In contrast, machinery in links like seeding, fertilizing, and pesticide spraying not only substitutes labor but also promotes technological progress in agricultural production, moving the production Frontier to a higher efficiency level, from Q to Q' , and thus reduces the distance to the optimal Frontier, with the production point shifting from A to A'' . In this process, smallholder farmers may not achieve the same technological transformation as large-scale farmers, leading to a shorter distance in the shift of their production points, from B to B' . This indicates that, compared to smallholder farmers, large-scale farmers gain greater benefits from technological progress.

Technological progress enhances the productivity advantages of large-scale farmers, and its impact on grain production is mainly reflected in improving the output level of each production factor. This indicates that, although an increase in farm size may be accompanied by a trend of declining yield per unit of land, farmers can still improve the output level of each production factor through technological progress, thereby alleviating or even reversing the “inverse relationship” between farm size and yield per unit. Therefore, neither of them constitutes a sufficient condition nor a necessary condition. To illustrate this point, this study constructs the following model:

$$q = \frac{Q}{T} = \varphi(T) \quad (1)$$

$$TFP = A = \frac{Q}{Input} = \frac{q}{\tau} \quad (2)$$

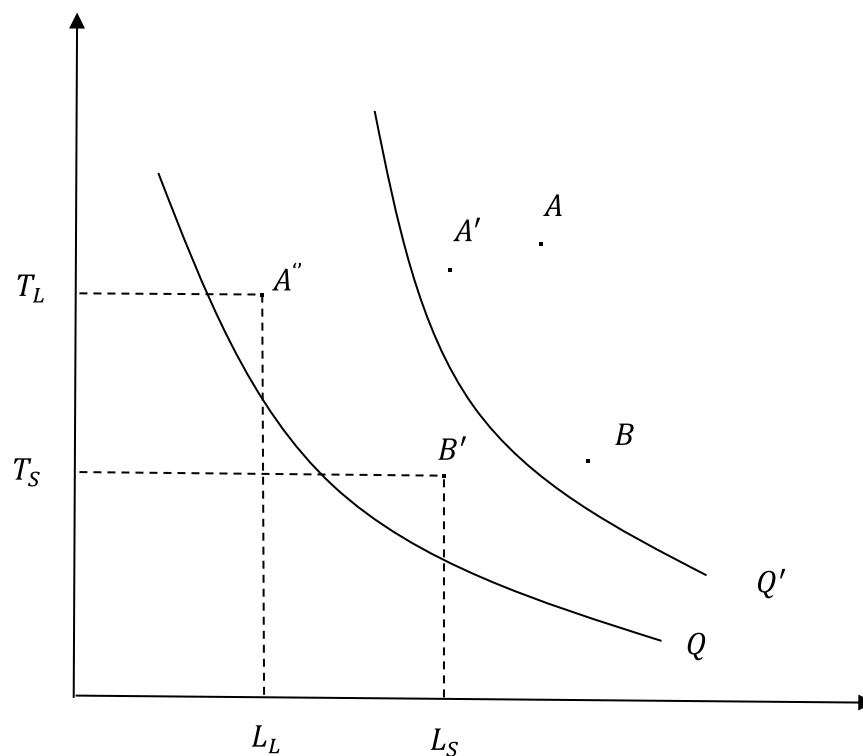


FIGURE 1
The impact of technological progress on farmers with different farm sizes.

In Equations 1, 2, q represents the land yield of grain, Q represents the total grain output of the farmer, T represents the farm size, and $\varphi(T)$ represents the function of land yield with respect to farm size. TFP denotes the total factor productivity at the farmer level, which is used to measure the farmer's technological level, and τ represents the factor input per unit of land (labor and capital). To demonstrate that technological progress related to farm size is not correlated with factor inputs, the study conducts the following analysis:

$$\frac{\partial TFP}{\partial T} = \frac{\partial(q/\tau)}{\partial T} = \frac{(\frac{\partial q}{\partial T})(\tau) - q(\frac{\partial \tau}{\partial T})}{\tau^2} \quad (3)$$

$$\begin{aligned} \frac{\partial TFP}{\partial T} &= \left(\frac{\partial q}{\partial T}\right)\left(\frac{1}{\tau}\right)\left[1 - \frac{q(\frac{\partial \tau}{\partial T})}{\tau(\frac{\partial q}{\partial T})}\right] = \left(\frac{\partial q}{\partial T}\right)\left(\frac{1}{\tau}\right)\left[1 - \left(\frac{\frac{\partial \tau}{\partial T}}{\frac{\tau}{q}}\right)\left(\frac{T}{q}\right)\left(\frac{\partial q}{\partial T}\right)\right] \\ \frac{\partial TFP}{\partial T} &= \left(\frac{\partial q}{\partial T}\right)\left(\frac{1}{\tau}\right)\left[\frac{\varepsilon_{q,T}}{\varepsilon_{q,T}} - \frac{\varepsilon_{\tau,T}}{\varepsilon_{q,T}}\right] \\ \frac{\partial q}{\partial T} &= \left(\frac{\partial TFP}{\partial T}\right)\tau\left[\frac{\varepsilon_{q,T}}{\varepsilon_{q,T} - \varepsilon_{\tau,T}}\right] \end{aligned}$$

As shown in Equation 3, $\varepsilon_{q,T}$ represents the land output elasticity, and $\varepsilon_{\tau,T}$ represents the returns to scale elasticity of factors. Based on the derived results, if there is an “inverse relationship” between farm size and land yield, i.e., $\varepsilon_{q,T} < 0$ and $\frac{\partial q}{\partial T} < 0$, then either Equations 4, 5 must hold (a similar analysis applies to the “positive relationship”). When Equation 4 holds, $\frac{\partial TFP}{\partial T} < 0$ indicates a negative relationship between technological progress and farm size, meaning that increasing the farm size would lower agricultural TFP . In this case, $\varepsilon_{q,T} < \varepsilon_{\tau,T}$ suggests

that as farm size expands, the rate of decrease in land yield per unit area is faster than the rate of decrease in factor input per unit area. When Equation 5 holds, $\frac{\partial TFP}{\partial T} > 0$ indicates a positive relationship between technological progress and farm size, meaning that expanding the farm size would increase agricultural TFP . In this case, $\varepsilon_{q,T} > \varepsilon_{\tau,T}$ suggests that as farm size expands, the rate of decrease in land yield per unit area is slower than the rate of decrease in factor input per unit area.

$$\frac{\partial TFP}{\partial T} < 0 \text{ and } \varepsilon_{q,T} < \varepsilon_{\tau,T} \quad (4)$$

$$\frac{\partial TFP}{\partial T} > 0 \text{ and } \varepsilon_{q,T} > \varepsilon_{\tau,T} \quad (5)$$

The above analysis indicates that although expanding the farm size leads to a decrease in marginal output, adopting new technologies can still improve land yield, thereby alleviating or even reversing the “inverse relationship” between farm size and land yield. Specifically, when the loss in yield due to farm size expansion exceeds the gain in yield from new technology, there will be an “inverse relationship” between farm size and land yield. Conversely, if the yield improvement from new technology outweighs the yield loss from farm size expansion, a “positive relationship” will emerge.

3 Model specification

The relationship between farm size and land yield is influenced by various factors. Although nonlinear models may better fit the

data in some cases, choosing a linear model, in the absence of sufficient evidence supporting a nonlinear relationship, requires fewer assumptions and can meet the needs of most econometric analyses. The key inputs for food production include land, capital, and labor, while differences in farmers' technological levels and production methods affect the output elasticity of these factors, thereby influencing the final yield level.

3.1 Theoretical model

Assuming that the key inputs for food production include land, capital, and labor, this study uses the Cobb-Douglas production function to analyze the relationship between farm size and land yield. The corresponding functional form can be expressed as:

$$Y_{it} = A_{it} T_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma} e^{\varepsilon_{it}} \quad (6)$$

In Equation 6, Y_{it} represents the total output of crop t planted by farmer i , where crop t includes wheat, maize, and rice. A_{it} denotes the technological level of farmer i in planting crop t , T_{it} represents land input, L_{it} represents labor input, and K_{it} represents capital input. The parameters α , β and γ represent the output elasticities of land, labor, and capital, respectively. Let $\theta = \alpha + \beta + \gamma$, e^{ε} represents exogenous production shocks. Dividing both sides of Equation 6 by the farm size and taking the logarithm, we obtain:

$$\ln \frac{Y_{it}}{T_{it}} = \ln(A_{it}) + (\theta - 1) \ln T_{it} + \beta \ln \left(\frac{L_{it}}{T_{it}} \right) + \gamma \ln \left(\frac{K_{it}}{T_{it}} \right) + \varepsilon_{it} \quad (7)$$

The farmer's technological level (A_{it}) is not only related to the farmer's household characteristics (X_{it}), but also has an endogenous relationship with the farm size, that is, $\ln(A_{it}) = \varphi(T_{it}, X_{it}) = v\bar{T}_{it} + \omega X_{it}$. Therefore, Equation 7 can be rewritten as:

$$\ln \left(\frac{Y_{it}}{T_{it}} \right) = v \ln(\bar{T}_{it}) + \omega X_{it} + (\theta - 1) \ln(T_{it}) + \beta \ln \left(\frac{L_{it}}{T_{it}} \right) + \gamma \ln \left(\frac{K_{it}}{T_{it}} \right) + \varepsilon_{it} \quad (8)$$

From Equation 8, it can be seen that the factors affecting land yield primarily include: technological progress related to farm size and household characteristics, returns to scale of production factors (proportional factor inputs), and factor inputs per unit of land (i.e., non-proportional factor inputs). If the factor market is in a perfectly competitive environment and the returns to scale of production factors are constant ($\theta = 1$), farmers, aiming for profit maximization, should apply the same amount and proportion of factor inputs per unit of land. In this case, the farm size is unrelated to the factor input ratio. Therefore, Equation 8 can be rewritten as:

$$\ln \left(\frac{Y_{it}}{T_{it}} \right) = v\bar{T}_{it} + \omega X_{it} + \varepsilon_{it} \quad (9)$$

Equation 9 is the classic yield model, which is widely used in the analysis of farm size and land yield (Assunção and Braido, 2007;

Barrett, 2010; Gourlay et al., 2019). As seen from Equation 8, the yield model actually identifies the impact of agricultural technological progress related to farm size on crop yield. Since this model is established under the assumption that there are no distortions in the factor market and that returns to scale are constant, there is a correlation between farm size, factor input ratios, and returns to scale. Therefore, although a large number of studies have proven the existence of an "inverse relationship," their results may contain some biases. In reality, the factor market is not in a perfectly competitive environment. When farmers expand their farm size, market imperfections lead to increased supervision costs for labor, resulting in a reduction in factor inputs per mu (Abay et al., 2019; Helfand and Taylor, 2021). To reduce the bias in the model results caused by market imperfections, the above equation can be modified by controlling for factor inputs per mu:

$$\ln \left(\frac{Y_{it}}{T_{it}} \right) = v\bar{T}_{it} + \omega X_{it} + \beta \ln \left(\frac{L_{it}}{T_{it}} \right) + \gamma \ln \left(\frac{K_{it}}{T_{it}} \right) + \varepsilon_{it} \quad (10)$$

Compared to Equation 9, Equation 10 considers the impact of market imperfections on the structure of factor inputs, i.e., the production function model (Julien et al., 2019; Rada et al., 2019; Aragón et al., 2022). In this case, the model bias is expressed as $\varepsilon_{it} = (\theta - 1) \ln T_{it} + \varepsilon'_{it}$. Assuming that $\bar{T}_{it} = T_{it}$, v' is used to identify the impact of agricultural technological progress related to farm size on crop yield, then $v = v' + (\theta - 1)$. In Equation 10, v represents the combined effect of technological progress and returns to scale of the factors of production¹. Since farmers with higher production technology levels can achieve more output with fewer factor inputs, technological progress related to farm size cannot be directly observed in Equation 10. Therefore, variables that can measure technological progress need to be included. Broadly speaking, agricultural technological progress includes not only the movement of the production Frontier (narrowly defined as agricultural technological progress) but also non-physical technological advancements such as technical efficiency (Gong et al., 2020). Farm size not only determines the size and technical level of agricultural machinery but also influences the conditions for machinery application and management efficiency (Kagin et al., 2016; Gautam and Ahmed, 2019). Therefore, when identifying the impact of technological progress on the relationship between farm

1 To facilitate explanation, most existing studies on the relationship between farm size and land yield per unit assume constant returns to scale (CRS) for the factors of production. However, in reality, returns to scale generally show a decreasing trend. Nevertheless, returns to scale cannot be incorporated as a variable in econometric models, which leads to potential bias in the coefficient for farm size. Despite this, the coefficient for farm size remains valuable for the following reasons: First, the diminishing returns to scale in agricultural production factors are widely accepted. While the coefficient for farm size may be biased to some extent, it can still provide a relatively clear overall trend and offers a reasonably valid explanation. Second, diminishing returns to scale are related to technological progress, and technological progress may be a result of decreasing returns to scale. Since it is difficult to evaluate the two factors independently, the combined effect is an acceptable outcome.

size and yield, both physical machinery technological advancements and losses in technical efficiency should be considered.

3.2 Econometric model

Traditional production functions tend to conflate the physical technological progress related to farm size with technical efficiency losses. Omitting the impact of technical efficiency can lead to bias in the relationship between farm size and land yield (Wang and Schmidt, 2002; Kumbhakar and Lovell, 2003). Based on Equation 10, this study constructs a stochastic Frontier analysis model.

$$\ln(q_{it}) = \alpha_0 + \alpha_1 \ln(T_{it}) + \alpha_2 \ln(l_{it}) + \alpha_3 \ln(k_{it}) + \sum_{k=1}^n \xi_k M_k + \sum_{k=1}^6 \eta_k M_k * T_{it} + \sum_{i=1}^n \delta_i Q_{it} + D_i + V_{it} - U_{it} \quad (11)$$

In this model, q_{it} represents the yield per unit area of crop t planted by farmer i , where crop t includes wheat, corn, and rice. T_{it} denotes the planting area of crop t by farmer i , while l_{it} and k_{it} represent the labor and capital inputs per mu, respectively. M_k represents the adoption of agricultural machinery technology in different production links, including cultivation, seeding, harvesting, fertilization, spraying, and irrigation. $M_k * T_{it}$ is the interaction term between machinery technology and planting area. Q_{it} represents land characteristic variables (land quality and slope), and D_i denotes the regional dummy variable. V_{it} represents exogenous shocks, while U_{it} represents the technical inefficiency term, used to measure the unobserved technical efficiency losses at the farm level. It is assumed that U_{it} follows a distribution of $N(\delta Z_{it}, \delta_u^2)$, where $u_{it} \geq 0$ and is independent of v_{it} , with V_{it} being the random disturbance term. The stochastic Frontier model allows the farm size variable to appear simultaneously in both the production function and the technical inefficiency term. The former identifies the optimal production Frontier determined by technological progress, while the latter identifies the technical efficiency related to the farm size, reflecting the ability of farms with different farm size to utilize existing production technology. Additionally, the application of agricultural technology not only requires farmers to have certain professional knowledge and skills but also needs the support of a socialized service system (Hu and Zhang, 2018; Yang et al., 2019). Therefore, in the technical efficiency term, this study constructs the following model:

$$U_{it} = \beta_0 + \beta_1 \ln(T_{it}) + \beta_3 \ln(S_{it}) + \sum_{i=1}^n \xi_i H_i + \varepsilon_{it} \quad (12)$$

In this model, T_{it} represents the planting area, while S_{it} denotes the degree of adoption of agricultural machinery socialized services by the farmer, measured by the ratio of the service operation area to the machinery operation area (Zhang et al., 2022). H_i represents the household characteristics of the farmer, including the age, education level, and employment status of the household head. Moreover, technical inefficiency losses differ across farmers with varying farm sizes, meaning that U_{it} does not satisfy the zero-mean assumption. This leads to bias when using ordinary least squares (OLS) for estimation. Therefore, maximum likelihood estimation (MLE) is required for analysis. Compared to OLS, MLE does not require

variables to be independent of each other, but only assumes that U_{it} and V_{it} are independent. Generally, maximum likelihood estimation allows for joint estimation of the parameters in both the production function and the inefficiency term in one step. Let σ_u^2 and σ_v^2 represent the variances of U_{it} and V_{it} , respectively, while σ_s^2 denotes the total variance in the model, where $\sigma_s^2 = \sigma_u^2 + \sigma_v^2$. The portion of the total variance attributed to technical inefficiency loss, σ_u^2/σ_s^2 , is denoted by γ . This value, which approaches 1, indicates that the gap between actual and potential maximum output is primarily due to technical inefficiency.

4 Empirical analysis

4.1 Data sources

The data in this study comes from the China Rural Revitalization Survey (CRRS), a nationwide rural tracking survey organized by the Institute of Rural Development, Chinese Academy of Social Sciences. The first phase of this survey was conducted in August–September 2020 across ten provinces (or autonomous regions): Guangdong, Zhejiang, Shandong, Anhui, Henan, Heilongjiang, Guizhou, Sichuan, Shaanxi, and Ningxia. The survey covered 50 counties (or cities) and 156 townships, collecting 300 village-level questionnaires and over 3,800 farmer-level questionnaires, involving more than 15,000 people. The survey content includes individual basic characteristics, education and employment status, family demographics, income and expenditure, crop planting structure and land transfer, as well as village population and organizational conditions, agricultural production and management.

The data cleaning process was conducted as follows: First, wheat, rice, and corn are China's primary grain crops, accounting for the vast majority of the country's grain production. This study selects farmers cultivating these three crops as the research sample, not only because of their significant role in agricultural production but also because their wide geographical distribution and varying farm sizes can effectively reflect the impact of different farm sizes on land yield. Second, to ensure the accuracy and reliability of the research results, the study implemented rigorous sample screening and processing. Specifically, samples with farm sizes exceeding five standard deviations were excluded to avoid the influence of outliers. Additionally, samples with missing values, anomalies, or farm sizes smaller than 1 mu (approximately 0.067 ha) were removed to ensure data completeness and representativeness. After these screening steps, the study ultimately obtained 2,871 valid samples, including 692 wheat-growing farmers, 652 rice-growing farmers, and 1,527 corn-growing farmers². This sample distribution not only covers different crop types but also reflects the cultivation characteristics of farmers with varying farm sizes. The specific distribution is shown in Table 1.

² The World Bank defines smallholder farmers and large-scale farmers based on a farm size of 30 mu (2 ha), and this study will also use this standard.

TABLE 1 The distribution of the farm size of the three major staple crops.

Farm size (mu)	1–10	10–30	30–50	50–100	100–200	>200	Samples
Wheat	499	146	15	14	10	8	692
Rice	508	54	16	27	26	21	652
Corn	1,030	289	80	71	24	33	1,527

4.2 Descriptive statistics of variables

The descriptive statistics of the main variables are shown in Table 2. In the sample of this study, the yields of wheat, rice, and corn farmers were 380.52 kg/mu, 463.64 kg/mu, and 431.04 kg/mu, respectively, which are close to the national average yield levels for the three major staple crops³. The sample contains a relatively high proportion of large-scale farmers, with the average farm sizes for wheat, rice, and corn farmers being 17.90 mu, 20.77 mu, and 24.33 mu, respectively. In terms of machinery adoption, the machinery rate for cultivation, seeding, and harvesting was relatively high, with over 90% mechanization in the wheat cultivation, seeding, and harvesting links, 81%, 68%, and 75% for rice, and 87%, 65%, and 82% for corn. The machinery rate for fertilizing and spraying was lower, especially for spraying, with 12% for wheat, 14% for rice, and 19% for corn. In terms of technical efficiency, the level of socialized agricultural machinery services for the three crops was approximately 30%, mainly benefiting from the development of the socialized agricultural machinery service system in recent years. The average age of household heads exceeded 55, indicating a clear trend of aging.

4.3 Regression results analysis

4.3.1 The impact of farm size on land yield

In the stochastic Frontier model, the production function section reflects the maximum output level that can be achieved with production factors under the best production method, while the technical efficiency section reflects the degree of diffusion and application of existing technology. This study uses the “one-step method” to simultaneously estimate both the production function and the technical efficiency section, avoiding the estimation bias caused by different distribution assumptions in the “two-step method.” In the empirical analysis, it is necessary to test the suitability of the stochastic Frontier model. Therefore, this paper constructs the following generalized likelihood ratio test model:

$$\lambda = -2[L(H_0) - L(H_1)] \quad (13)$$

As shown in Equation (13), among them, $L(H_0)$ is the log-likelihood value under the null hypothesis, $L(H_1)$ is the log-likelihood value under the alternative hypothesis, and λ is the

likelihood ratio statistic, which is used to compare with the critical value of the chi-square distribution. This paper conducts likelihood ratio tests on the stochastic Frontier production function in Equation 11 and the efficiency loss term in Equation 12. The maximum likelihood values are -160.79 , -184.93 , -167.11 , and -170.78 , respectively, and the γ values are 0.804, 0.838, 0.913, and 0.920, respectively, all reaching the 1% significance level. This indicates that the random disturbance term mainly comes from the technical efficiency loss term, and the model specification is appropriate.

Table 3 presents the regression results on the impact of farm size on land yield for wheat. The results in column (1) indicate that, without controlling for land characteristic variables, expanding the farm size significantly reduces wheat yield per unit of land, and the result passes the 5% significance test. After adding land characteristic variables, the results in column (2) show no significant change, suggesting that land quality does not alter the relationship between farm size and land yield. When machinery technology variables are further included, the results in column (3) show that the “inverse relationship” weakens, with the coefficient for farm size changing from -0.52 to -0.047 , and statistical significance improving from 10% to 5%. Specifically, machinery in seeding and fertilization significantly improves land yield. In column (4), after adding the interaction term between farm size and machinery technology, the regression results indicate that the interaction between farm size and machinery in harvesting, fertilization, and spraying significantly enhances land yield. In the technical efficiency section, the coefficient for farm size is negative, indicating that increasing farm size helps reduce technical efficiency losses. The level of agricultural machinery socialization services and the education level of the household head both effectively reduce technical efficiency losses. Overall, land characteristics have a limited impact on the relationship between farm size and land yield, while agricultural machinery technology plays a significant role.

Table 4 reports the relationship between rice farm size and land yield. In the production function section, the regression results in columns (1) and (2) show that the expansion of farm size significantly reduces rice yield per unit of land, passing the 1% significance test. This result does not change with the inclusion of land characteristic variables. After introducing machinery technology variables in column (3), although farm size still significantly negatively affects rice land yield, the coefficient decreases from -0.062 to -0.053 , with significance only at the 10% level. Specifically, mechanized seeding and fertilization significantly improve land yield. The regression results in column (4) show that the interaction terms between mechanized seeding and fertilization and farm size are significantly positive, while the interaction term for mechanized spraying is also positive, but only passes the 10% significance level. In the technical

³ In 2020, the National Bureau of Statistics of China released data showing that the yield per mu for wheat was 383 kg, for rice was 470 kg, and for corn was 421 kg.

TABLE 2 Descriptive statistics of farmer-level variables.

Variable name	Variable description	Wheat		Rice		Corn	
		Mean	Sd	Mean	Sd	Mean	Sd
Dependent variable							
land yield	average Grain Yield per Mu (kg per Mu)	380.52	320.48	463.64	201.15	431.04	385.06
Independent variable							
farm size	crop planting area (in mu)	17.90	23.11	20.77	25.04	24.33	17.86
Factor input							
household labor	household labor input (person-hours per mu)	23.80	19.34	31.95	25.67	24.51	34.48
hired labor	hired labor input (person-hours per mu)	8.03	16.13	11.55	25.24	7.12	23.52
seed fee	self-purchased seed cost (yuan per mu)	60.16	54.84	71.46	52.96	57.43	82.09
pesticide fee	cost of purchasing insecticides, herbicides, and fungicides (yuan per mu)	82.86	112.93	90.57	60.15	85.02	92.81
fertilizer fee	self-purchased fertilizer cost (yuan per mu)	154.23	318.67	167.64	274.85	121.87	143.66
machinery and utilities fee	cost of machinery services, irrigation, and water and electricity expenses (yuan per mu)	124.35	87.48	142.13	113.86	117.34	89.52
Land characteristic variables							
soil quality	0 = Poor; 1 = Moderate; 2 = Good	1.35	0.72	1.83	0.69	1.57	1.26
land leveling	1 = flat land; 0 = Slope land or Lowland	0.69	0.54	0.73	0.36	0.81	0.42
Adoption of machinery technology							
cultivation	adoption of agricultural machinery (0 = No; 1 = Yes)	0.92	0.32	0.81	0.15	0.87	0.26
harvesting		0.94	0.57	0.75	0.12	0.82	0.11
irrigation		0.51	0.28	0.62	0.49	0.44	0.20
seeding		0.91	0.52	0.68	0.41	0.65	0.29
fertilization		0.24	0.08	0.31	0.12	0.35	0.24
spraying		0.12	0.05	0.14	0.03	0.19	0.16
Technical inefficiency term							
socialized machinery services	The proportion of the area serviced by machinery in the total area of mechanized crops (average across different production links)	0.34	0.23	0.37	0.56	0.34	0.26
age	Actual age of the household head (in years)	54.13	69.01	57.13	72.35	52.09	54.85
education	Years of education of the household head (in years)	6.84	11.06	7.02	8.83	7.86	9.05
employment status	1 = full-time farming,2 = part-time farming	1.25	1.05	1.36	0.62	1.14	0.91

TABLE 3 The regression results of wheat on land yield.

Variable name	Dependent variable: Land yield per unit (ln)			
	(1)	(2)	(3)	(4)
Production Function Section				
farm size (ln)	−0.068**	−0.052**	−0.047*	0.071
	(0.029)	(0.024)	(0.025)	(0.055)
household labor input (ln)	0.048	0.055	0.073	−0.074
	(0.042)	(0.051)	(0.049)	(0.052)
hired labor input (ln)	−0.028**	−0.037**	−0.021*	−0.023*
	(0.014)	(0.016)	(0.011)	(0.012)
capital input (ln)	0.197*	0.203*	0.246	0.248
	(0.141)	(0.120)	(0.199)	(0.175)
mechanized cultivation			−0.102	0.084
			(0.095)	(0.075)
mechanized seeding			0.074**	−0.059
			(0.031)	(0.052)
mechanized harvesting			−0.142	0.091
			(0.095)	(0.081)
mechanized fertilization			0.060*	−0.089
			(0.034)	(0.077)
mechanized spraying			−0.214	0.118
			(0.155)	(0.087)
mechanized irrigation			0.059	0.124
			(0.043)	(0.103)
farm size* mechanized cultivation				−0.104
				(0.087)
farm size* mechanized seeding				0.015
				(0.011)
farm size* mechanized harvesting				0.037*
				(0.035)
farm size* mechanized fertilization				0.053**
				(0.025)
farm size* mechanized spraying				0.138**
				(0.065)
farm size* mechanized irrigation				0.069
				(0.045)
good soil quality		0.258	0.248	0.209
		(0.195)	(0.184)	(0.126)
moderate soil quality		0.062	0.078	0.072
		(0.048)	(0.065)	(0.068)

(Continued on following page)

TABLE 3 (Continued) The regression results of wheat on land yield.

Variable name	Dependent variable: Land yield per unit (ln)			
	(1)	(2)	(3)	(4)
whether it is flat land		−0.015***	−0.011***	−0.012**
		(0.005)	(0.004)	(0.005)
province dummy variables	Yes	Yes	Yes	Yes
constant	16.603***	14.352***	15.355***	16.087***
	(0.836)	(1.541)	(1.603)	(1.653)
Technical Inefficiency Section				
farm size (ln)	−0.060*	−0.063**	−0.052**	−0.045**
	(0.035)	(0.030)	(0.026)	(0.020)
socialized machinery services	−0.504*	−0.459**	−0.472**	−0.409*
	(0.293)	(0.214)	(0.236)	(0.213)
age	0.002	0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
education	−0.034**	−0.030*	−0.021*	−0.024*
	(0.015)	(0.016)	(0.012)	(0.013)
employee status	0.093	0.088	0.102	0.103
	(0.063)	(0.078)	(0.082)	(0.085)
constant	5.468***	7.207***	8.918***	8.040***
	(0.483)	(0.600)	(0.712)	(0.785)
σ_s^2	4.883***	4.475***	3.103***	3.594***
	(0.540)	(0.521)	(0.834)	(0.732)
γ	0.804***	0.838***	0.913***	0.920***
	(0.130)	(0.156)	(0.274)	(0.235)
likelihood	−160.79	−184.93	−167.11	−170.78
observations	652	652	652	652

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

inefficiency section, the coefficient for farm size is negative, consistent with the results for wheat. Additionally, part-time farmers increase technical inefficiency losses. The γ values are 0.848, 0.841, 0.860, and 0.810, indicating that the technical inefficiency component has strong explanatory power (The method is as described above).

Table 5 reports the regression results on the impact of corn farm size on land yield. In the production function section, the regression results in column (1) show that farm size significantly reduces land yield, but only at the 10% significance level. In column (2), after adding land characteristic variables, the coefficient for farm size shows no significant change. Column (3) reveals that, after introducing machinery technology variables, the coefficient for farm size shifts from negative to positive, with significance improving to the 5% level. Specifically, mechanized seeding, fertilization, and irrigation significantly increase corn land yield. The regression results in column (4) show that the interaction terms between farm size and mechanized seeding, fertilization, and

spraying are positive and significant. Overall, the adoption of machinery technology significantly increases land yield and reverses the “negative relationship” between farm size and land yield. In the technical efficiency section, the coefficient for farm size is negative, consistent with the results for wheat and rice. The coefficient for mechanized social services is also negative and significant, while the employment status of farmers significantly impacts technical efficiency. Part-time farmers experience greater technical efficiency losses. The γ values are 0.827, 0.848, 0.910, and 0.924, indicating that the technical efficiency component has enhanced explanatory power for the random disturbances (The method is as described above).

4.3.2 The impact of farm size on technological progress

In the technical efficiency section, the coefficient for farm size only represents the direction of the impact, rather than the degree of impact. To accurately identify the effect of farm size on land yield, it

TABLE 4 The regression results of rice on land yield.

Variable name	Dependent variable: Land yield per unit (ln)			
	(1)	(2)	(3)	(4)
Production Function Section				
farm size (ln)	−0.088***	−0.062***	−0.053*	0.038
	(0.041)	(0.024)	(0.028)	(0.025)
Factor input				
household labor input (ln)	0.019	0.021	0.014	0.015
	(0.016)	(0.014)	(0.010)	(0.013)
hired labor input (ln)	−0.027	−0.018	−0.031*	−0.028*
	(0.019)	(0.021)	(0.017)	(0.015)
capital input (ln)	0.069**	0.089**	0.072*	0.075*
	(0.032)	(0.038)	(0.041)	(0.043)
mechanized cultivation			−0.066	0.051
			(0.043)	(0.032)
mechanized seeding			0.043*	0.056
			(0.025)	(0.044)
mechanized harvesting			0.027	−0.052
			(0.025)	(0.037)
mechanized fertilization			0.081**	−0.012
			(0.040)	(0.008)
mechanized spraying			0.038	−0.025
			(0.031)	(0.054)
mechanized irrigation			−0.071	0.045
			(0.058)	(0.029)
farm size* mechanized cultivation				−0.090
				(0.055)
farm size* mechanized seeding				0.015***
				(0.004)
farm size* mechanized harvesting				0.037
				(0.031)
farm size* mechanized fertilization				0.053***
				(0.018)
farm size* mechanized spraying				0.081*
				(0.045)
farm size* mechanized irrigation				−0.026
				(0.019)
good soil quality		−0.118	−0.108	−0.124
		(0.115)	(0.131)	(0.118)

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TABLE 4 (Continued) The regression results of rice on land yield.

Variable name	Dependent variable: Land yield per unit (ln)			
	(1)	(2)	(3)	(4)
moderate soil quality		0.065	0.052*	0.057**
		(0.055)	(0.028)	(0.026)
whether it is flat land		−0.004***	−0.003***	−0.003***
		(0.000)	(0.000)	(0.000)
province dummy variables	Yes	Yes	Yes	Yes
constant	11.362***	10.352***	8.045***	8.158***
	(0.486)	(0.776)	(0.956)	(0.915)
Technical Inefficiency Section				
farm size (ln)	−0.181*	−0.205*	−0.277**	−0.175*
	(0.102)	(0.114)	(0.115)	(0.098)
socialized machinery services	−0.275	−0.240	−0.231	−0.282
	(0.196)	(0.188)	(0.185)	(0.190)
age	0.000	0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
education	0.005	0.007	0.008	0.011
	(0.004)	(0.005)	(0.006)	(0.009)
employee status	0.037**	0.035**	0.044**	0.043**
	(0.016)	(0.015)	(0.018)	(0.017)
constant	11.641***	9.342***	13.735***	13.065***
	(0.773)	(0.616)	(0.685)	(0.681)
σ_s^2	4.883***	4.475***	4.103***	4.594***
	(0.840)	(0.821)	(0.814)	(0.801)
γ	0.848***	0.841***	0.860***	0.810***
	(0.045)	(0.038)	(0.061)	(0.062)
likelihood	−164.05	−153.32	−267.59	−266.09
observations	692	692	692	692

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

is necessary to combine the coefficient for farm size in the production function section with the coefficient in the technical efficiency component. Therefore, this study adopts the methods of Battese and Broca (1997) and Wang and Schmidt (2002) to parametrize the technical efficiency loss component⁴.

$$\frac{\partial \ln E\left(\frac{Y_i}{T_{it}}\right)}{\partial \ln(T_{it})} = \beta_1 - C_i \left(\frac{\partial \mu_i}{\partial \ln(T_{it})} \right) \tag{14}$$

4 The specific calculation methods and procedures are based on (Belotti et al., 2013).

$$C_{it} = 1 - \frac{1}{\sigma} \left(\frac{\varphi\left(\frac{\mu_{it}}{\sigma} - \sigma\right)}{\Phi\left(\frac{\mu_{it}}{\sigma} - \sigma\right)} - \frac{\varphi\left(\frac{\mu_{it}}{\sigma}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma}\right)} \right) \tag{15}$$

As shown in Equation 14 and 15, in this context, $\frac{\partial \ln E\left(\frac{Y_i}{T_{it}}\right)}{\partial \ln(T_{it})}$ represents the output elasticity of land yield with respect to farm size in Equation 12, while β_1 represents the coefficient for farm size in the production function of the stochastic Frontier model. $\frac{\partial \mu_i}{\partial \ln(T_{it})}$ represents the “output elasticity” of technical efficiency with respect to farm size. φ and Φ represent the probability density function and cumulative distribution function of the standard normal distribution, respectively, and μ_{it} represents technical efficiency. C_{it} is the correction factor for technical efficiency, with values ranging between 0 and 1. The effect of farm size on technical efficiency loss is parameterized through the correction factor C_{it} .

TABLE 5 The regression results of corn on land yield.

Variable name	Dependent variable: Land yield per unit (ln)			
	(1)	(2)	(3)	(4)
Production Function Section				
farm size (ln)	−0.124*	−0.132*	0.085**	0.098*
	(0.071)	(0.084)	(0.042)	(0.057)
household labor input (ln)	0.058	0.065	0.062	0.063
	(0.037)	(0.045)	(0.042)	(0.040)
hired labor input (ln)	−0.041	−0.036	−0.033	0.034*
	(0.034)	(0.029)	(0.028)	(0.026)
capital input (ln)	0.498* (0.290)	0.554* (0.304)	0.508* (0.287)	0.441* (0.258)
mechanized cultivation			−0.031	0.074
			(0.023)	(0.061)
mechanized seeding			0.052*	0.101
			(0.027)	(0.092)
mechanized harvesting			0.066	−0.024
			(0.052)	(0.037)
mechanized fertilization			0.062**	0.104
			(0.028)	(0.087)
mechanized spraying			−0.072	−0.082
			(0.058)	(0.067)
mechanized irrigation			0.026**	0.082
			(0.012)	(0.075)
farm size* mechanized cultivation				−0.117
				(0.095)
farm size* mechanized seeding				0.204*
				(0.118)
farm size* mechanized harvesting				0.172
				(0.143)
farm size* mechanized fertilization				0.065***
				(0.023)
farm size* mechanized spraying				0.058***
				(0.018)
farm size* mechanized irrigation				0.104
				(0.097)
good soil quality		0.234	0.227	0.215
		(0.182)	(0.189)	(0.185)
moderate soil quality		0.118**	0.123	0.121
		(0.055)	(0.082)	(0.087)

(Continued on following page)

TABLE 5 (Continued) The regression results of corn on land yield.

Variable name	Dependent variable: Land yield per unit (ln)			
	(1)	(2)	(3)	(4)
whether it is flat land		−0.010*	−0.012**	−0.014**
		(0.006)	(0.006)	(0.006)
province dummy variables	Yes	Yes	Yes	Yes
constant	7.086***	7.646***	6.702***	6.160***
	(0.583)	(0.482)	(0.550)	(0.576)
Technical Inefficiency Section				
farm size (ln)	−0.135*	−0.142*	−0.183**	−0.175**
	(0.078)	(0.083)	(0.091)	(0.082)
socialized machinery services	−0.176***	−0.181***	−0.211***	−0.193***
	(0.054)	(0.061)	(0.078)	(0.062)
age	0.001	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
education	−0.014*	−0.015*	−0.013**	−0.012**
	(0.008)	(0.008)	(0.005)	(0.005)
employee status	0.023***	0.020***	0.019***	0.018***
	(0.007)	(0.006)	(0.006)	(0.006)
constant	8.903***	8.611***	8.121***	8.236***
	(0.476)	(0.403)	(0.593)	(0.560)
σ_s^2	3.110***	2.952***	3.193***	3.550***
	(0.750)	(0.675)	(0.597)	(0.574)
γ	0.827***	0.848***	0.910***	0.924***
	(0.196)	(0.209)	(0.214)	(0.275)
likelihood	−145.88	−158.41	−177.12	−178.34
observations	1,527	1,527	1,527	1,527

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

σ represents the standard deviation of μ_{it} , and $\frac{\varphi(\frac{\mu_{it}}{\sigma})}{\Phi(\frac{\mu_{it}}{\sigma})}$ represents the “relative position” of the standardized technical efficiency loss in the normal distribution. The closer C_{it} is to 1, the stronger the effect of farm size on land yield through the technical efficiency component. Table 6 reports the coefficients of the farm size after correction for the three main crops. Columns (1), (2), and (3) correspond to the regression results of the first three columns of the stochastic Frontier model discussed earlier. After correction, the coefficients of farm size for wheat and rice remain negative, but the “inverse relationship” is alleviated. The originally “negative relationship” for corn is partially alleviated, while the “positive relationship” is further strengthened. The above analysis indicates that land characteristics have a limited impact on the relationship between farm size and land yield, whereas agricultural machinery technology is closely related to farm size. The adoption of machinery technology effectively alleviates or even reverses the “inverse relationship” between the size of food crop

farming and land yield. For smallholder farmers, machinery technology mainly serves as a substitute for labor. As the farm size expands, the impact of machinery technology on land yield varies across different production links. Compared to labor-intensive links, machinery technology in control-intensive links can significantly increase land yield and shift the production Frontier. After considering the impact of technical efficiency, the “inverse relationship” between farm size and land yield for wheat and rice is further alleviated, while the “positive relationship” for corn is further strengthened. Meanwhile, in terms of the efficiency of machinery technology utilization, larger farmers have a natural advantage. Ignoring differences in farmers’ technical levels may lead to biases in the relationship between farm size and land yield. Larger farmers, as “early adopters” of technology, have an advantage in the application of new technologies, while smallholder farmers have failed to keep up and are further from the optimal production Frontier.

TABLE 6 The adjustment of the farm size coefficients for the three crops.

	(1)	(2)	(3)
Wheat			
production function	−0.068**	−0.052*	−0.047*
Technical efficiency term (parameterization)	0.045**	0.033**	0.037**
Corrected coefficients	−0.023**	−0.019**	−0.010
rice			
production function	−0.088**	−0.062**	−0.053***
Technical efficiency term (parameterization)	0.054**	0.046**	0.031**
Corrected coefficients	−0.034**	−0.016**	−0.022***
corn			
production function	−0.124*	−0.132	0.085**
Technical efficiency term (parameterization)	0.077***	0.064***	0.038***
Corrected coefficients	−0.047*	−0.068	0.123**

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

4.3.3 Robustness test

In order to identify the impact of machinery technology at different production links on the relationship between farm size and land yield, this study introduces a dummy variable for machinery technology, reflecting the differences between farmers of different farm sizes in adopting or not adopting machinery at specific links. However, when farmers choose machinery technology, they not only consider whether or not to adopt the technology, but also decide the level of machinery based on their farm size. This leads to potential differences in factors such as the amount of investment and usage frequency, even when the same machinery technology is adopted. Therefore, this study uses the per-mu machinery cost at different production links as a proxy variable for machinery technology and conducts robustness checks on the regression results. The regression results are shown in Table 7. In the production function section, after adding per-mu machinery costs, the relationship between farm size and land yield for the three main staple crops does not change significantly. In the technical efficiency section, the expansion of farm size significantly reduces technical efficiency loss. Overall, the regression results remain robust after replacing machinery technology.

In order to further control for regional differences in resource endowments, this study replaces provincial-level dummy variables with city-level dummy variables to ensure the stability of the econometric model. The results in Table 8 show that the “inverse relationship” between the farm size and land yield still exists for the three crops. Compared to power-intensive links such as cultivation, harvesting, and irrigation, the interaction term between machinery technology in seeding, fertilizing, and spraying application is significantly positive, indicating that the adoption of machinery technology significantly enhances the productivity of large-scale farmers. Overall, the impact of machinery technology on the relationship between farm size and crop land yield remains consistent across regions, confirming the robustness of the research findings.

5 Further analysis

This study conducts a correlation analysis of the relationship between farm size, input factors, and the adoption of machinery technology. As shown in Table 9, with the expansion of farm size, household labor input per mu for wheat, rice, and corn decreases, while hired labor input per mu increases, indicating that farmland scale management relies on a certain proportion of hired labor. The input of seeds, pesticides, and fertilizers decreases, while machinery and water-electricity costs increase. Regarding the adoption of machinery technology, with the expansion of farm size, the machinery levels of traditional cultivation, seeding, and harvesting links for the three crops significantly improve, while there are larger variations in the machinery levels for fertilizing, pesticide application, and irrigation. Specifically, wheat has a higher level of machinery in the fertilization links, rice shows a more pronounced machinery in both fertilization and irrigation links, and corn exhibits higher machinery in the fertilizing and spraying links.

Wheat has a shorter growth period and strong adaptability to the environment, requiring larger power-driven equipment for cultivation and harvesting. Power-intensive machinery ensures the stability and continuity of operations, but due to the relatively simple growth characteristics of wheat, the effect of control-intensive technology on improving yield is weaker. Rice, which requires a large amount of water and often grows in muddy environments, needs machinery with sufficient power to ensure efficient operations, especially in the transplanting links, where power-intensive machinery is crucial for improving operational efficiency. Corn has a longer growth period, deeper roots, and is more sensitive to climate and soil conditions. The proper application of control-intensive machinery technology is essential. Control-intensive technology not only enhances planting precision but also optimizes production conditions and finely tunes the growth process, significantly improving corn land yield, with results superior to those for wheat and rice.

TABLE 7 Robustness test (replace machinery technology measurement method).

Variable name	Wheat		Rice		Corn	
	(1)	(2)	(3)	(4)	(5)	(6)
Production function section						
farm size (ln)	−0.057**	−0.049	−0.066**	0.042	0.103*	−0.078
	(0.023)	(0.046)	(0.031)	(0.037)	(0.055)	(0.065)
mechanized cultivation	−0.095	−0.093	−0.071	−0.062	0.028	0.041
	(0.087)	(0.085)	(0.055)	(0.048)	(0.019)	(0.035)
mechanized seeding	0.068***	−0.054	0.059**	0.051	0.064**	−0.093
	(0.024)	(0.038)	(0.027)	(0.041)	(0.030)	(0.065)
mechanized harvesting	0.107	0.082	0.034	−0.057	−0.051	−0.024
	(0.087)	(0.075)	(0.030)	(0.045)	(0.052)	(0.037)
mechanized fertilization	0.114**	−0.105	0.102***	−0.033	0.062**	0.058*
	(0.055)	(0.089)	(0.037)	(0.029)	(0.028)	(0.031)
mechanized spraying	0.183	0.104	0.017	−0.021	−0.024	−0.025
	(0.162)	(0.090)	(0.014)	(0.016)	(0.017)	(0.020)
mechanized irrigation	0.040	0.084	−0.024*	0.011	0.076*	−0.061
	(0.032)	(0.091)	(0.012)	(0.008)	(0.044)	(0.054)
farm size* mechanized cultivation		0.035		−0.104*		0.084
		(0.026)		(0.055)		(0.069)
farm size* mechanized seeding		0.023**		0.021***		0.174**
		(0.010)		(0.007)		(0.082)
farm size* mechanized harvesting		0.033		−0.084		0.158
		(0.028)		(0.065)		(0.122)
farm size* mechanized fertilization		0.047**		0.093**		0.030**
		(0.016)		(0.044)		(0.019)
farm size* mechanized spraying		0.117***		0.044***		0.025***
		(0.044)		(0.015)		(0.011)
farm size* mechanized irrigation		0.096		−0.034		−0.081
		(0.085)		(0.025)		(0.074)
Factor input	control	control	control	control	control	control
Land characteristic	control	control	control	control	control	control
province dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
constant	15.355***	16.087***	8.621***	8.028***	8.083***	8.871***
	(1.295)	(1.283)	(0.891)	(0.807)	(0.810)	(0.758)
Technical inefficiency term						
Farm size	−0.062**	−0.058**	−0.219**	−0.193*	−0.174***	−0.175***
	(0.030)	(0.024)	(0.104)	(0.102)	(0.064)	(0.065)
Control variable	control	control	control	control	control	control
constant	5.028***	6.922***	11.946***	12.882***	8.010***	8.540***

(Continued on following page)

TABLE 7 (Continued) Robustness test (replace machinery technology measurement method).

Variable name	Wheat		Rice		Corn	
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.451)	(0.584)	(0.568)	(0.605)	(0.573)	(0.684)
σ_s^2	3.012***	3.590***	4.596***	4.705***	3.193***	3.550***
	(0.729)	(0.784)	(0.784)	(0.772)	(0.523)	(0.514)
γ	0.826***	0.859***	0.805***	0.863***	0.893***	0.904***
	(0.147)	(0.172)	(0.215)	(0.226)	(0.355)	(0.361)
likelihood	−157.46	−173.05	−247.18	−235.72	−164.59	−167.55
observation	652	652	692	692	1,527	1,527

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

To further identify the relationship between the machinery technology in different production links and the technical level of farmers, this study estimates the Total Factor Productivity (TFP) of 2,871 sample farmers using the Solow residual method. The farmers are then divided into five groups according to their farm sizes, with the mean values taken for each group (Sheng et al., 2015; Wang et al., 2020). The specific calculation method is as follows:

$$Y_{ij} = \alpha \ln T_{ij} + \beta \ln K_{ij} + \gamma \ln L_{ij} + D_p + \varepsilon_{ij} \quad (16)$$

$$\ln(TFP_{ij}) = Y_{ij} - \hat{\alpha} \ln T_{ij} - \hat{\beta} \ln K_{ij} - \hat{\gamma} \ln L_{ij} - D_p - \varepsilon_{ij} \quad (17)$$

As shown in Equation 16, 17, Y_{ij} represents the total output of crop j planted by farmer i ; T_{ij} represents the land input of crop j planted by farmer i , measured by the planting area of the crop; K_{ij} represents the capital input of crop j planted by farmer i , including costs for seeds, fertilizers, pesticides, and agricultural machinery services; L_{ij} represents the labor input of crop j planted by farmer i , measured by the labor hours contributed by the farmer in the crop planting process. D_p represents the fixed effects, ε_{ij} represents the random disturbance term, and α , β , and γ represent the output elasticities of land, capital, and labor, respectively. $\ln(TFP_{ij})$ represents the total factor productivity level of crop j planted by farmer i .

The regression results in Table 10 show that the land output elasticities for the three grain crops are 27.8%, 30.6%, and 34.1%, respectively, while the labor input elasticities are 10.9%, 16.5%, and 18.4%, respectively. The capital input elasticities are 45.0%, 31.5%, and 29.8%, respectively. Overall, the output elasticity of labor is relatively small, while the output elasticity of capital is relatively high, indicating that capital and intermediate goods play an increasingly important role in grain production.

The analysis shows that for wheat, TFP increases with the expansion of farm size, reaching its maximum between 100 and 200 mu, but decreases beyond 200 mu (As shown in Figure 2). For sizes below 10 mu, the impact of machinery on TFP at different links is not significant, but as the farm size increases, machinery in harvesting, fertilization, and spraying significantly improves TFP. For rice, the TFP index is highest in the 30–100 mu range and declines beyond 100 mu (As shown in Figure 3). As the farm size expands, machinery in seeding, fertilization, and irrigation significantly enhances TFP. In corn production, TFP increases

with farm size, although the growth rate slows after 200 mu (As shown in Figure 4). Machinery in spraying, fertilization, and seeding has a strong effect on improving TFP. In conclusion, the impact of Machinery technology on TFP varies across different crops and links. As the farm size increases, machinery in labor-intensive links such as seeding, spraying, and fertilization has a more significant effect on enhancing farmers' TFP.

Overall, the expansion of farm size helps improve farmers' technical levels, but its effect has certain limits. The peak TFP index for wheat and rice is found in the 100–200 mu and 30–100 mu ranges, respectively. Beyond these ranges, farmers' TFP indices begin to decline. While the TFP index for corn continues to grow with the expansion of farm size, the growth trend becomes less pronounced beyond 200 mu. In terms of the adoption of machinery, when farmers have a small farm size, the impact of machinery in different production links on technical levels is not significant. However, once the farm size exceeds a certain threshold, machinery in seeding, fertilization, and spraying has a significant impact on farmers' technical levels, while machinery in cultivation, harvesting, and irrigation shows less impact. This suggests that, comparatively, power-intensive machinery technologies have a greater effect on labor substitution and cost reduction in grain production, while control-intensive machinery technologies play a more significant role in promoting farmland scale management.

6 Discussion

This study reveals that while farmland scale management significantly increases land yield through the adoption of more advanced machinery technologies, large-scale farmers still exhibit certain productivity disadvantages compared to smallholder farmers. This discrepancy may be related to the prevalence of left-behind elderly and women in rural China. In the absence of sufficient non-agricultural employment opportunities, surplus labor increases labor input and management precision per unit of land, factors that cannot be fully captured by the model. This study aligns with the findings of Otsuka et al. (2016), Liu and Violette. (2016), and Foster and Rosenzweig (2022), indicating that the adoption of machinery technologies effectively mitigates the “inverse

TABLE 8 Robustness test (replace dummy variable).

Variable name	Wheat		Rice		Corn	
	(1)	(2)	(3)	(4)	(5)	(6)
Production function section						
farm size (ln)	−0.062**	−0.069**	−0.072*	−0.077*	0.129*	0.178*
	(0.029)	(0.033)	(0.042)	(0.041)	(0.075)	(0.101)
mechanized cultivation	−0.087	−0.093	−0.071	−0.062	0.028	0.021
	(0.072)	(0.088)	(0.065)	(0.051)	(0.036)	(0.038)
mechanized seeding	0.065**	0.051**	0.062*	0.058*	0.065**	0.088*
	(0.031)	(0.023)	(0.033)	(0.032)	(0.028)	(0.045)
mechanized harvesting	0.114	0.089	0.037	0.048	−0.053	−0.026
	(0.146)	(0.116)	(0.052)	(0.061)	(0.046)	(0.031)
mechanized fertilization	0.121	0.102	0.095**	0.037*	0.059**	0.055*
	(0.096)	(0.105)	(0.042)	(0.021)	(0.027)	(0.028)
mechanized spraying	−0.139	−0.120	0.015	−0.012	−0.021	−0.023
	(0.155)	(0.142)	(0.018)	(0.011)	(0.018)	(0.021)
mechanized irrigation	0.056	0.071	−0.045*	0.047	0.066*	0.062
	(0.042)	(0.082)	(0.024)	(0.056)	(0.035)	(0.059)
farm size* mechanized cultivation		−0.064		−0.273*		−0.148
		(0.054)		(0.142)		(0.087)
farm size* mechanized seeding		0.072**		0.086***		0.109**
		(0.010)		(0.007)		(0.082)
farm size* mechanized harvesting		0.053		−0.072		0.059
		(0.031)		(0.078)		(0.068)
farm size* mechanized fertilization		0.117**		0.194**		0.054***
		(0.056)		(0.093)		(0.020)
farm size* mechanized spraying		0.238**		0.051**		0.036***
		(0.114)		(0.023)		(0.012)
farm size* mechanized irrigation		−0.175		−0.145		−0.104
		(0.147)		(0.216)		(0.086)
factor input	control	control	control	control	control	control
land characteristic	control	control	control	control	control	control
city dummy variables	Yes	Yes	Yes	Yes	Yes	Yes
constant	14.034***	13.754***	9.667***	9.911***	8.106***	8.237***
	(1.972)	(1.173)	(1.307)	(1.516)	(1.763)	(1.438)
Technical inefficiency term						
farm size	−0.037**	−0.042**	−0.195**	−0.184*	−0.175***	−0.168***
	(0.015)	(0.018)	(0.098)	(0.105)	(0.062)	(0.061)
control variable	control	control	control	control	control	control

(Continued on following page)

TABLE 8 (Continued) Robustness test (replace dummy variable).

Variable name	Wheat		Rice		Corn	
	(1)	(2)	(3)	(4)	(5)	(6)
constant	6.846***	6.657***	10.724***	10.346***	9.861***	9.337***
	(0.982)	(0.934)	(0.813)	(0.783)	(0.604)	(0.655)
σ_s^2	3.012***	3.590***	4.596***	4.705***	3.193***	3.550***
	(0.535)	(0.549)	(0.560)	(0.573)	(0.416)	(0.457)
γ	0.840***	0.819***	0.834***	0.843***	0.886***	0.925***
	(0.098)	(0.105)	(0.164)	(0.124)	(0.238)	(0.218)
likelihood	−148.36	−157.31	−238.09	−227.13	−188.73	−176.62
observation	652	652	692	692	1,527	1,527

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

TABLE 9 The relationship between crop farm size, input factors and the adoption of machinery technology.

Variable name	Household labor	Hired Labor	Seed Costs	Pesticide costs	Fertilizer costs	Machinery costs
	(1)	(2)	(3)	(4)	(5)	(6)
wheat farm size	−0.065***	0.271***	−0.088*	−0.111**	−0.334**	0.129***
	(0.048)	(0.101)	(0.047)	(0.056)	(0.167)	(0.046)
rice farm size	−0.121***	0.340***	−0.054	−0.027*	−0.592*	0.082***
	(0.042)	(0.128)	(0.036)	(0.014)	(0.358)	(0.031)
corn farm size	−0.088***	0.291***	−0.408*	−0.326***	−0.592***	0.245***
	(0.033)	(0.106)	(0.221)	(0.116)	(0.218)	(0.092)
variable name	mechanized cultivation	mechanized seeding	mechanized harvesting	mechanized fertilization	mechanized spraying	mechanized irrigation
	(7)	(8)	(9)	(10)	(11)	(12)
wheat farm size	0.112*	0.274***	0.218**	0.349*	0.073	0.471
	(0.082)	(0.085)	(0.115)	(0.203)	(0.052)	(0.380)
rice farm size	0.238**	0.149***	0.410***	0.258*	0.318	0.145***
	(0.104)	(0.053)	(0.121)	(0.145)	(0.293)	(0.058)
corn farm size	0.065**	0.445***	0.173	0.203**	0.296**	−0.084
	(0.031)	(0.129)	(0.109)	(0.101)	(0.128)	(0.077)

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.

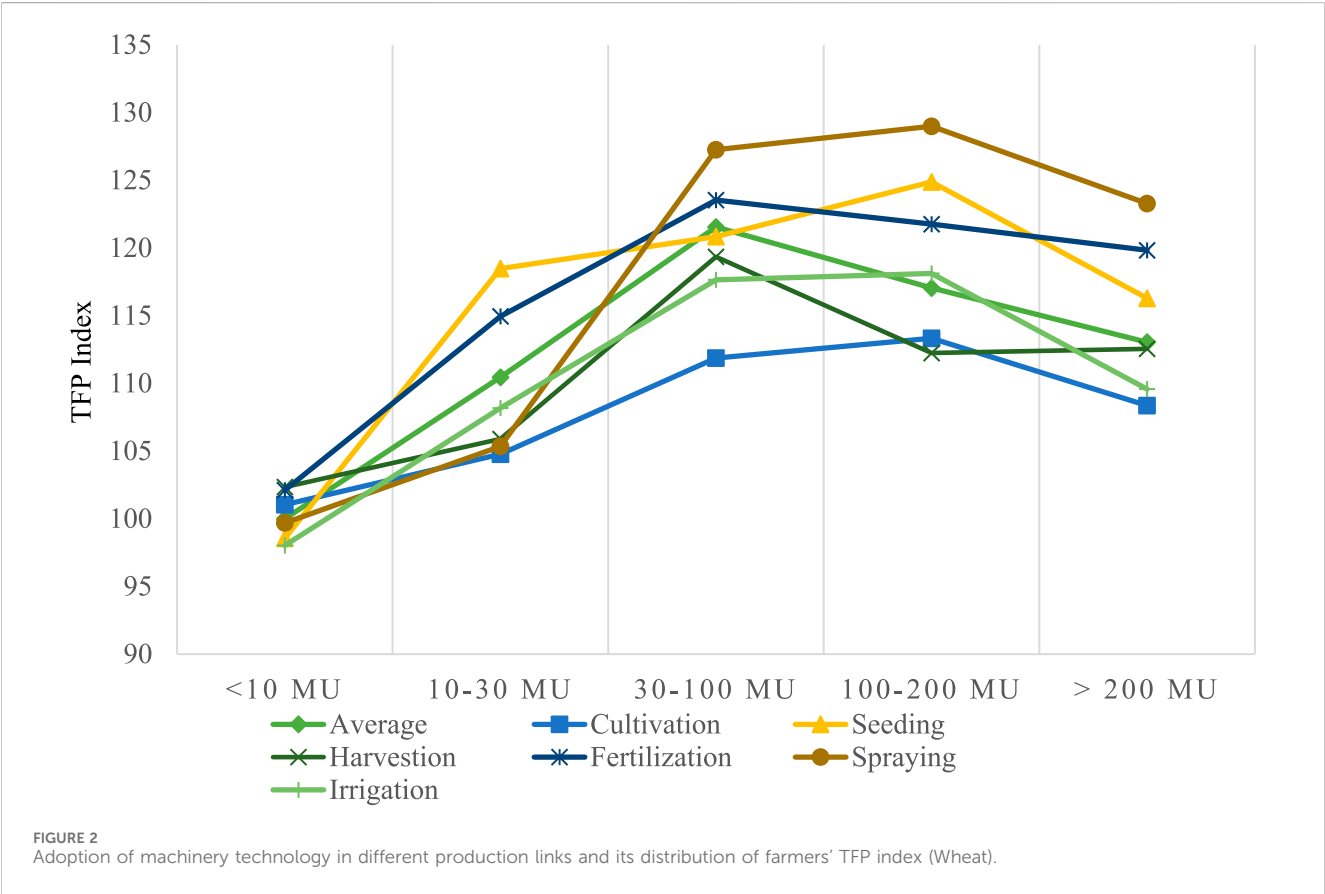
relationship” between farm size and land yield. However, this study further highlights that machinery technologies in different links of production have varying emphases on factor substitution and technological progress. For instance, machinery in control-intensive links such as seeding, fertilization, and spraying is more effective in shifting the production Frontier, particularly for large-scale farmers, whereas machinery in traditional links like cultivation and harvesting primarily substitutes labor and has a relatively limited impact on increasing grain yields. Although control-intensive machinery technologies offer greater advantages in

terms of yield improvement and potential, their adoption rate among farmers remains relatively low. This is primarily due to the fact that control-intensive machinery technologies need to be integrated with advanced biotechnologies, requiring higher levels of technical expertise and operational skills, which significantly increases the cost of adoption. For example, the price of precision fertilization machinery (100,000 to 300,000 yuan) and spraying drones (100,000 to 200,000 yuan) is typically several times higher than that of cultivation and harvesting machinery (30,000 to 50,000 yuan).

TABLE 10 The output elasticity of production factors at the farmer level.

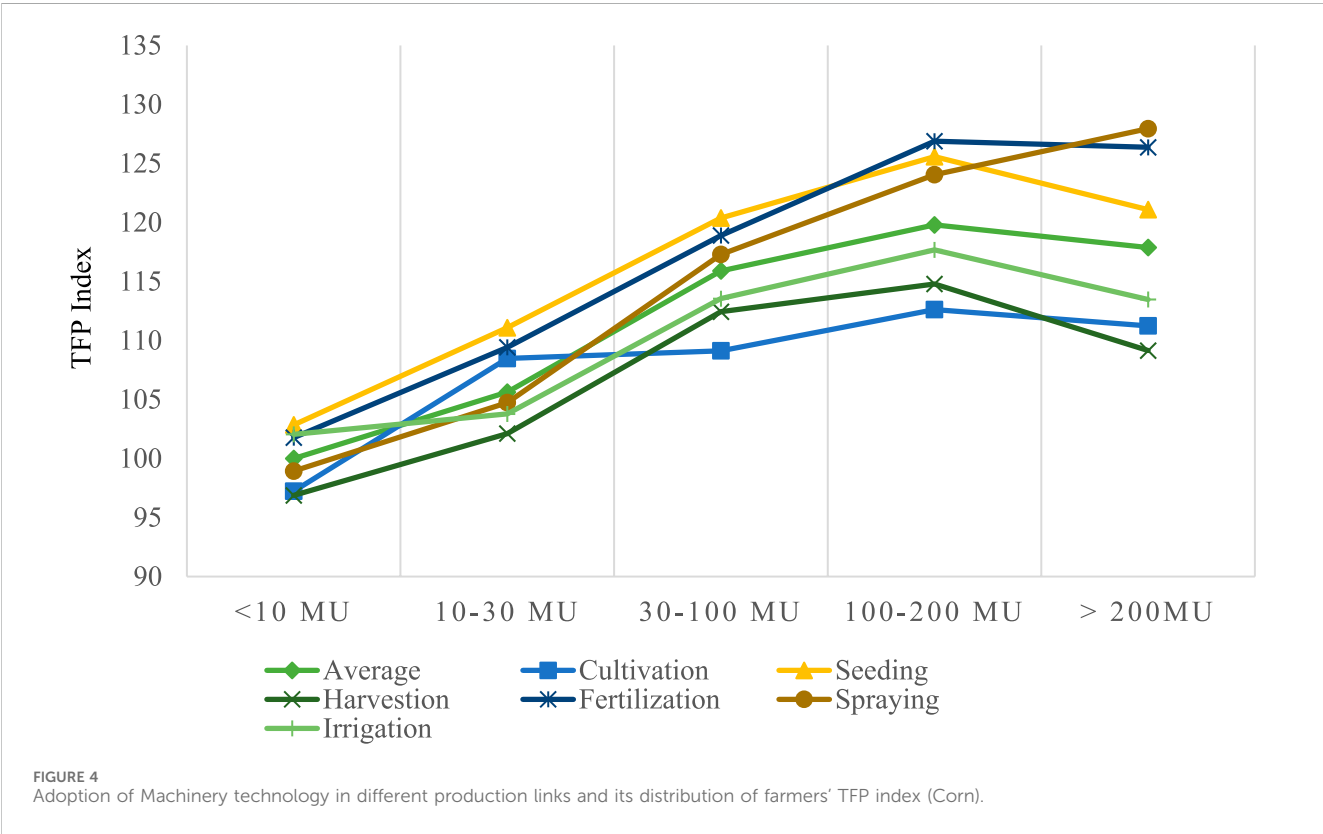
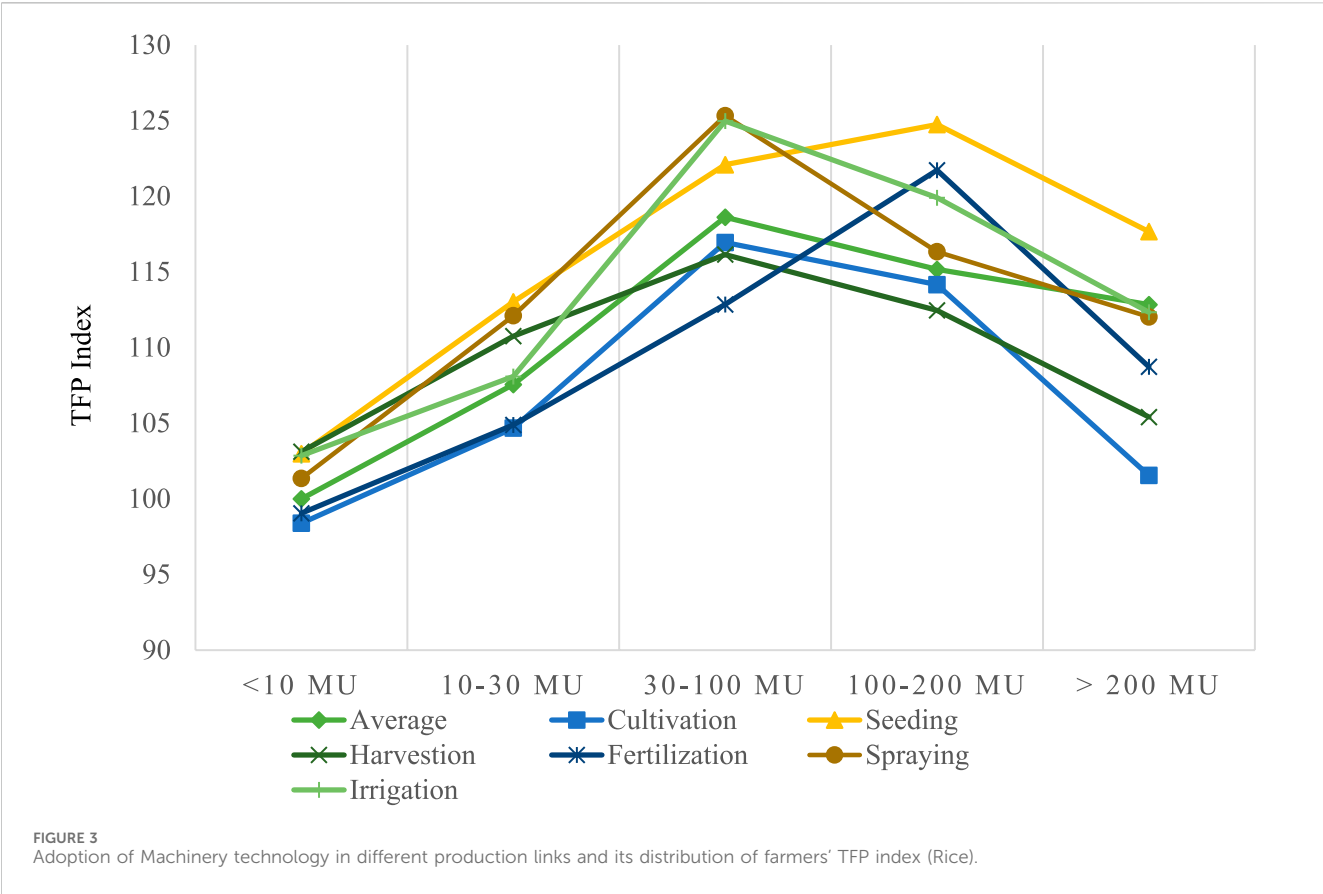
Variable name	Ln (total yeild)		
	Wheat	Rice	Corn
land	0.278***	0.306***	0.341***
	(0.084)	(0.093)	(0.095)
labor	0.109***	0.165***	0.184***
	(0.033)	(0.042)	(0.047)
capital	0.450***	0.315***	0.298***
	(0.104)	(0.074)	(0.081)
province dummy variables	control	control	control
R ²	0.752	0.845	0.825
observation	652	692	1,527

Note: *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are shown in parentheses.



Additionally, compared to smallholder farmers, large-scale farmers are not only more likely to adopt new machinery technologies but also demonstrate higher efficiency in utilizing these technologies, operating closer to the production Frontier. This conclusion differs from the findings of Kagin et al. (2015) in Mexico and Bangladesh, where large-scale farmers faced greater difficulties in accessing modern agricultural machinery due to poor

infrastructure and transportation conditions, resulting in lower technical efficiency. This discrepancy may be attributed to China's rapidly developing agricultural machinery socialization service system, which has effectively increased the adoption rate of mechanization among farmers. Consequently, large-scale farmers can compensate for their productivity disadvantages through the widespread application of machinery technologies. The limitations



of this study include: First, the research sample only includes cross-sectional data from 1 year. Although the sample has a high proportion of large-scale farmers, the lack of long-term time-series data prevents an assessment of the dynamic impact of machinery technology advancements on the relationship between farm size and crop yield over different time periods. Second, although machinery technologies have the potential to mitigate or even reverse the “inverse relationship,” their adoption methods include purchasing agricultural machinery and purchasing machinery services. However, this study does not distinguish between the differences of these two approaches.

7 Research conclusion and policy recommendations

Farmland scale management is an important means of increasing farm household income and advancing agricultural modernization. However, whether its development poses a threat to China's food security still requires further examination. A popular view in development economics suggests a classic “inverse relationship” between farm size and land yield. However, with the advancement of agricultural Machinery technology, this view may be challenged. The impact of farm size on land yield is a result of the combined effects of changes in returns to scale, marginal factor inputs, and technological progress. Existing research primarily focuses on the substitution effect of machinery technology on labor, with insufficient characterization of technological progress related to farm size, which may lead to biases in studies on the relationship between farm size and land yield. Building on this, our study further identifies the significant role of agricultural machinery in promoting technological advancement. This not only deepens the multidimensional understanding of agricultural machinery but also provides new perspectives and insights for the theoretical exploration of farmland scale management. The research findings indicate that, prior to incorporating machinery technology variables, an “inverse relationship” existed between farm size and land yield for wheat, rice, and corn. After introducing the machinery technology variables, the coefficient for wheat farm size changed from -0.052 to 0.047 , the coefficient for rice farm size shifted from -0.062 to -0.053 , and the coefficient for corn farm size transformed from -0.132 to 0.085 . This demonstrates that machinery technology has reversed the “inverse relationship” for corn, while only mitigating it for wheat and rice. Furthermore, after considering the impact of technical efficiency loss and adjusting the farm size coefficient, the relationship between farm size and crop yield does not show significant changes. In specific production links, when farm size is small, machinery mainly serves as a substitute for labor in various production links. However, as the farm size expands, machinery in control-intensive links (as opposed to power-intensive links) becomes more beneficial for increasing crop yield.

The farmland scale management is not in conflict with high yields per unit of land. However, the development of large-scale

farming relies on advancements in machinery technology. Expanding the farm size helps with the application of new technologies and increases crop yields, thereby ensuring food security in China. However, there are limits to the development of farmland scale management, and excessively large sizes may not be conducive to efficient food production. Therefore, moderate-scale farming not only aligns with China's “large population and limited land” resource endowment, but also helps increase farmers' incomes and ensures food security. Against the backdrop of a declining agricultural labor force, the mechanization of power-intensive production links has been widely adopted, significantly enhancing the stability of agricultural production. However, the application of control-intensive machinery technologies, such as precision fertilization and drone-based plant protection, involves higher costs and demands greater technical skills and knowledge, which limits their adoption among smallholder farmers. Although these technologies can significantly improve production efficiency and resource utilization, their high initial investment and operational costs pose economic barriers for many farmers. To promote the adoption of control-intensive machinery technologies, the government should reduce farmers' input costs through policy subsidies. First, differentiated subsidy policies should be provided for farmers of different farms, with priority given to small and medium-sized farmers. Second, technical training and support should be offered alongside subsidies to help farmers master the operation and maintenance skills of control-intensive machinery technologies.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WZ: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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