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Agricultural socialized services empowering smallholder rice producers to achieve high technical efficiency: empirical evidence from southern China

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Introduction: This study emphasizes the importance of agricultural efficiency for food security and income generation, especially among smallholder rice farmers in southern China. Limited access to essential agricultural services hinders productivity in this region. The study highlights the significant potential of agricultural socialized services (ASS) in improving the technical efficiency of smallholder rice production.

Methods: To analyze the impact of ASS on technical efficiency in rice production, we focused on tillage, transplanting, crop protection, and harvest operations. We employed stochastic frontier analysis and collected data from smallholder farmers in Hunan, Jiangxi, and Zhejiang provinces. By estimating the technical efficiency of rice production, we aimed to assess the relationship between ASS and smallholder farmers' technical efficiency.

Results and discussion: The results of our analysis revealed that ASS significantly enhance the technical efficiency of rice production among smallholder farmers by supporting agricultural practices such as transplanting, crop protection, and harvest operations. However, we found that the impact of ASS on tillage operations was not statistically significant. Participation in ASS enhances smallholders' access to modern production techniques, resources, and knowledge, leading to improved technical efficiency. These services also empower smallholder rice producers to adopt sustainable farming practices, access credit, financing, and market information, and promote collective action and cooperation, ultimately influencing technical efficiency.

Conclusion: This study emphasizes the potential of ASS in improving the technical efficiency of smallholder rice production in southern China. Policymakers and agricultural organizations can use these insights to design interventions that promote efficient practices, enhance productivity, support livelihoods, and ensure food security in the region.

KEYWORDS

agricultural socialized services, smallholder farmers, rice production, technical efficiency, stochastic frontier analysis

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1 Introduction

Rice is the cornerstone of global food security, providing sustenance for over half of the world's population. The United Nations General Assembly has highlighted the significance of rice in addressing poverty and achieving sustainable food security (United Nations General Assembly, 2002). The majority of agricultural production worldwide occurs on small farms, with approximately 90% of the 570 million farms globally being classified as small, meaning they are less than 2 hectares in size. These small farms are cultivated by around 1.5 billion of the world's economically disadvantaged population (Rapsomanikis, 2015). Agricultural smallholders contribute approximately 30–34% of the global food supply, utilizing only 24% of the total agricultural land area (Ricciardi et al., 2018). Interestingly, despite their smaller size compared to commercialized large farms, smaller farms yield higher volumes of crops on average (Ricciardi et al., 2021). Of particular note is the significant contribution of small rice farm holders to the global rice supply, as they are responsible for producing the majority of the rice consumed worldwide (Giller et al., 2021). However, research indicates that there is a rice yield gap and proposes a solution: increasing rice production by 32% and reducing excess nitrogen through targeted improvements in inefficient cropping systems and addressing yield gaps (Shen et al., 2021). Therefore, targeting smallholder rice producer, through institutional innovations, natural resource management practices, and training can improve the economic well-being of smallholder farmers (Mishra et al., 2022). These interventions drive sustainable agricultural development, increasing productivity, resilience, and food security, while empowering smallholders to revolutionize rice production for an equitable and sustainable future (Djuraeva et al., 2023).

Smallholder farmers play a crucial role in the agricultural sector, particularly in regions like Southern China, where rice cultivation is a significant economic activity. For instance, Hunan, Jiangxi, and Zhejiang provinces are well-known as the main rice-producing areas in in southern China, collectively accounting for about 25% of the country's total rice production. However, these farmers often face numerous challenges, including limited access to resources, outdated farming techniques, and inadequate information (Ren et al., 2023). Agricultural socialized services (ASS) have emerged as potential solutions to address these challenges, encompassing various support mechanisms such as cooperative farming, shared machinery, training programs, and knowledge sharing platforms (Chen et al., 2022). By providing access to modern technologies, improved seeds, advanced irrigation practices, and effective pest management strategies, these services have the potential to break down barriers that hinder smallholder farmers' productivity and profitability. Additionally, they promote collective action and collaboration among farmers, fostering a supportive network that enables the exchange of ideas and best practices (Wang and Huan, 2023). Southern China, with its diverse landscape and high concentration of smallholder rice producers, provides an ideal context to investigate the impact of ASS on technical efficiency (Shi et al., 2023).

ASS refer to outsourcing of agricultural production and operation activities, emphasizing market-oriented attributes. It differs from the planned economic system's agricultural service system. In China, the shift from planned to market-oriented economy influenced ASS development. ASS includes pre-production, in-production, and post-production services. Pre-production involves agricultural material supply and breeding. In-production includes technical training, field management, and machinery operations. Post-production encompasses processing, storage, transportation, and marketing (Zang et al., 2022). The primary objective of ASS is to bridge the information and resource gap between farmers and scientific advancements in agriculture, ultimately increasing productivity and competitiveness. These services, including technology extension, crop cultivation guidance, pest control, irrigation management, and financial support, are tailored to the specific needs of farmers and designed to promote sustainable and efficient agricultural practices (Liu et al., 2022). By providing access to modern farming techniques, advanced technologies, and professional expertise, ASS plays a crucial role in rural development, fostering agricultural innovation and reducing poverty (Olmedo et al., 2023). It is imperative to investigate the impact of ASS on smallholder rice farmers in southern China to understand its potential for enhancing technical efficiency and addressing the challenges faced by farmers.

Various research studies have explored the determinants of technical efficiency (TE) among smallholder farmers from different perspectives. For instance, it has been found that adopting agricultural green production technology can enhance TE, as observed in studies such as (Li et al., 2021) and (Lampach et al., 2021). However, limited accessibility to these technologies can undermine their effectiveness. Participation in agricultural extension services has also been linked to higher TE levels, as reported in (Biswas et al., 2021). Additionally, membership in agricultural cooperatives has been found to contribute to greater TE, as indicated in (Ma et al., 2018). Disparities in TE among farmers have been attributed to several factors, such as access to credit, soil fertility, social capital, plot distance, access roads, and extension services, as demonstrated in the analysis by Binam et al. (2004). Moreover, studies have found that farm size (Dagar et al., 2021), precision agriculture (Carrer et al., 2022), land ownership (Ngango and Hong, 2021), education, hands-on experience, climate change adaptation strategies and crop variety (Mzyece and Ng'ombe, 2021), and reliable financing (Chandio et al., 2019) are all significant contributors to TE. Alwarritzi et al. (2015) also points out that the group dynamics of farmers, extension programs, educational levels, and farm diversification are influential factors that determine technical efficiency. While previous research has examined various determinants of technical efficiency among smallholder farmers, there is a gap in the existing literature regarding the role of ASS in empowering smallholder rice producers and their impact on achieving high levels of technical efficiency, specifically in the context of southern China.

This study seeks to (a) address how ASS contributes to rice production in southern China, (b) understand the impact of ASS on the TE efficiency of smallholders' rice production and its variation across agricultural practices, and (c) provide decision-makers guidance and information on the appropriate interventions to implement for increased productivity and efficiency. Specifically, this study will assess the impacts of ASS on tillage, transplanting, crop protection, and harvest operations.

Investigating the relationship between these services and farmers' productivity, this study can provide valuable insights and fill gaps in current literature. Theoretically, this research expands our understanding of the factors that influence smallholder farmers' TE and productivity. It explores the role of ASS as a potential mechanism for improving farmers' access to resources, knowledge, and technology. The findings can contribute to theories related to collective action, knowledge sharing, and cooperative farming models. Additionally, this study can shed light on the applicability and effectiveness of these services in the context of smallholder rice production in Southern China, adding nuance to existing theoretical frameworks. Empirically, the study generates evidence on the impact of ASS on smallholder farmers' technical efficiency. By conducting a rigorous analysis of data collected from farmers in Southern China, this research can provide quantitative evidence of the positive effects of these services on productivity. The findings can support policy decisions by informing policymakers and agricultural extension agencies about the potential benefits of investing in and promoting ASS. Furthermore, this empirical evidence can contribute to the design and implementation of targeted interventions aimed at improving smallholder farmers' access to these services. By identifying the specific aspects of ASS that have the greatest impact on TE, policymakers and practitioners can tailor their interventions to maximize the benefits for smallholder rice producers. This empirical research can also serve as a basis for further studies and comparisons in different regions or agricultural contexts, expanding our knowledge in the field.

The remainder of this study is organized as follows: Section two presents a literature review and theoretical analysis, providing a comprehensive overview of the relevant research and theoretical frameworks. Section three outlines the materials and methods employed in this study, describing the data collection process and analytical techniques used. In section four, the results of the study are presented and discussed, offering insights and interpretations of the findings. Finally, section five concludes the study by summarizing the main findings and their implications for policies and future research directions.

2 Literature review and theoretical analysis

2.1 Literature review

Academic research on TE in agriculture has its roots in the broader field of agricultural economics. The concept of technical efficiency emerged as a way to measure and evaluate the productive efficiency of agricultural systems, particularly in terms of how efficiently inputs are transformed into outputs (Ruggiero, 2000; Meijers, 2009).

The context of literature on the TE of rice production mainly includes the following aspects. (1) Studies explore the determinants and dynamics of TE level in rice production systems and provide insights into strategies for improvement such as access to resources, technological advancements, adaptability to shocks, off-farm work, land fragmentation, gender differences, organic farming practices, policy changes, processing techniques, personality traits, technology adoption, and external effects from other industries (Xu and Jeffrey, 1998; Yao and Shively, 2007; Mkanthama et al., 2018; Ali et al., 2020; Wang et al., 2020; Rabbany et al., 2022). (2) The studies utilize various approaches to examine different dimensions of efficiency, including technical, allocative, cost, and scale efficiencies, as well as profitability, resource productivity, and knowledge impact (Coelli T et al., 2005; Coelli TJ et al., 2005; Pedroso et al., 2018; Nguyen et al., 2019; Sissoko et al., 2022). (3) In terms of research method, studies shifted from qualitative approaches to empirical analysis such as Stochastic Frontier Analysis (SFA), data envelopment analysis (DEA), meta-regression analysis (MRA), Bayesian stochastic frontier approach, Panel Data Analysis and other empirical approaches (Pede et al., 2018; Ho et al., 2021; Chaovanapoonphol et al., 2022). In recent years, Stochastic frontier models offer a comprehensive analysis of efficiency levels. Studies utilizing these models highlight the distributional assumptions associated with the TE estimation process and identify determinants of efficiency in rice production.

The literature review on the technical efficiency (TE) of smallholder rice farmers reveals several factors that influence their efficiency levels. Technological advancements, as highlighted by Sissoko et al. (2022), have a positive impact on productivity, especially in irrigated rice production. Access to essential resources such as water, infrastructure, and inputs, as emphasized by Li et al. (2020), plays a crucial role in enhancing efficiency. The ability to adapt to unexpected changes in production conditions, identified by Ho and Shimada (2019), is another key factor contributing to higher TE levels. Farmers who can swiftly adjust demonstrate increased efficiency. Engaging in off-farm work, as found by Chang and Wen (2010), shows a positive association with TE among rice farmers. This association is possibly due to improved income and better risk management capabilities. However, the actual influence of off-farm work on TE may be relatively negligible in terms of its impact on efficiency. Enhancing access to modern agricultural technologies and practices, stressed by Xu and Jeffrey (1998), is vital for improving TE. It is understood that access to modern technologies contributes to higher efficiency levels. Similarly, Tan et al. (2010) recognized the consolidation of fragmented land holdings as a contributing factor to enhanced TE in rice production. Land consolidation efforts are significant for improving efficiency. Additionally, Oladeebo and Fajuyigbe (2007) explored gender differences in TE and underscored potential disparities between male and female farmers. This highlights the necessity for gender-responsive strategies to improve efficiency. The literature suggests that technological advancements, access to essential resources, adaptability, access to modern agricultural technologies, land consolidation, and gender disparities are all factors influencing the TE of smallholder rice farmers. ASS have been a topic of study in recent years due to their potential to improve farming practices and support smallholder farmers in China. Several studies have explored various aspects of ASS, including adoption rates and their relationship with relative poverty levels and risks (Binam et al., 2004), the impact of ASS on environmentally friendly practices such as the use of fertilizers in rice production (Endalew et al., 2022), and their contribution to protecting cultivated land and promoting sustainable land management (Ogada et al., 2014). Other studies have examined the effectiveness of ASS in reducing chemical fertilizer use and how farm size moderates this relationship (Khanal et al., 2018), the influence of risk perception on farmers' adoption of organic fertilizer practices and the role of ASS in overcoming barriers to adoption (Viengpasith et al., 2012), and the contribution of ASS to production efficiency within agriculture (Cheng et al., 2022). Maintenance skill training has been found to give ASS providers an advantage, as it enables them to provide better services to farmers (Odhiambo et al., 2004), while internet use has been found to be an important factor in farmers' adoption of ASS (Shi et al., 2023). Supply chain scheduling optimization has been explored in the context of ASS platforms, highlighting the importance of coordination and efficiency in the delivery of services (Li, 2015).

The role of ASS in promoting sustainable agricultural practices among smallholder farmers has also been studied (Huan et al., 2022), as has their impact on collective action among farmers in managing irrigation systems (Cai et al., 2022). Research has also examined the impact of ASS on farmland scale management behavior among smallholder rice farmers in southern China (Yi et al., 2019) and on the use of chemical fertilizers among wheat smallholders, specifically examining the mediating role of ASS (Qian et al., 2022). Agricultural machinery ASS has been found to positively impact land productivity within the Chinese context (Cheng et al., 2022), while motivations for smallholder farmers to utilize ASS for farmland scale management have been explored from the perspective of collective action (Danso-Abbeam, 2022). A study on socialized care services for the elderly in rural China found that willingness to purchase such services was influenced by factors such as income level and health status (Zhu et al., 2022). Overall, as indicated in Figure 1, while the studies differ in their specific focus, they collectively emphasize the potential of agricultural support systems (ASS) to support farmers in various aspects of their farming practices, including production efficiency, sustainable agriculture, and land management.

In conclusion, the existing literature on ASS in China has provided valuable insights into various aspects such as adoption rates, environmental practices, land management, and collective action among smallholder farmers. However, one notable gap in the literature is the lack of investigation into the impact of ASS on the TE of smallholder rice farmers. ASS have the potential to play a crucial role in enhancing TE by providing farmers with access to modern machinery, training on best practices, and timely information. Understanding the impact of ASS on the TE of smallholder rice farmers is important for several reasons. In addition to increasing productivity and profitability for farmers, which can contribute to poverty reduction and rural development, it can also promote sustainable agriculture by ensuring optimal resource utilization and reducing waste. Moreover, addressing this research gap can help to tackle the challenges faced by smallholder farmers, including labor shortage and limited access to modern technologies. Exploring the impact of ASS on the TE of smallholder rice farmers can provide valuable insights into the effectiveness of these services in improving farming practices and optimizing resource allocation. This research gap needs to be addressed to further enhance our understanding of the potential benefits and limitations of ASS in China's rural agricultural sector.

2.2 Theoretical analysis

The concept of TE in agricultural production involves assessing a farmer's ability to maximize output using agricultural input factors under specific technical conditions (Li and Ito, 2023). Although ASS is not typically considered an input factor in agricultural production, they can still have a significant impact on the TE of smallholder rice producers in Southern China. This is especially important given the decline of family human capital in rural areas, as ASS organizations can help compensate for this through the provision of professional technicians, modern equipment and tools (Chen et al., 2023). By changing the allocation structure of input factors, small farmers can utilize the advantages of these services to improve output and, in turn, increase their agricultural TE. Previous research by Shi et al. (2023) and Huan et al. (2022) has highlighted the positive impact of ASS on smallholder rice producers in China. Therefore, with reference to the analysis framework proposed by Takeshima (2016), it can be inferred that farmers who avail of ASS will likely exhibit improved levels of

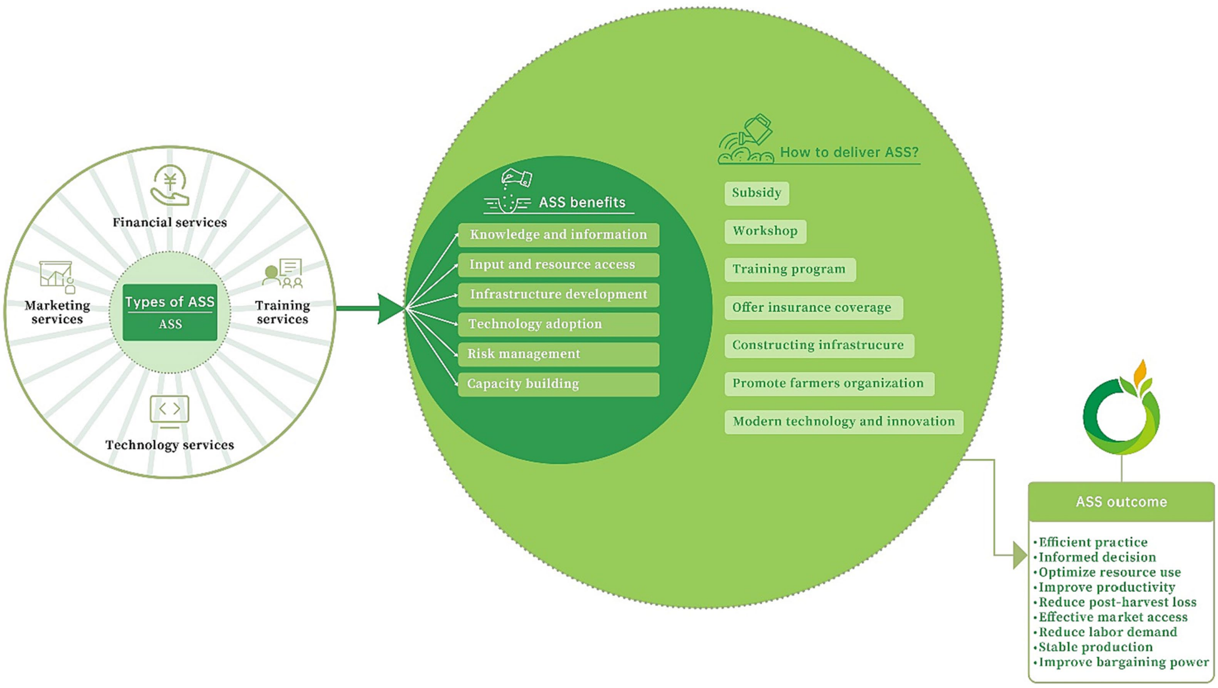

FIGURE 1
The mechanism how ASS affect TE.

output and TE compared to those who do not and show the following status:

$$f_1\left(K_1;X\right) \text{if } S=1 \tag{1}$$

$$f_0\left(K_0;X\right) \text{if } S=0$$

In Eq. 1, FS is the production function, y is the output, KS is the input factor vector, s is whether small farmers have purchased ASS, and X is the economic and social factor vector affecting agricultural output. In Eq. 2, farmers will maximize utility based on the following profit maximization conditions:

$$\max U\left(\pi\right) \tag{2}$$

$$\text{S.ks}$$

$$\pi = S\times\left[f_1\left(K_1;X\right)-c1\left(w;k1\right)\right]+\left(1-S\right) \times\left[f_0\left(K_0;X\right)-c0\left(w;k0\right)\right] \tag{3}$$

In Eq. 3, CS (W; KS) is the cost function and W is the price of all input factor vectors. In the process of pursuing utility maximization, farmers will be subject to the following budget constraints:

$$gs\left(ks, X, w, \cdot\right)\geq 0,\forall S \tag{4}$$

In Eq. 4, η It is a variable vector affecting farmers' budget constraints. Farmers' optimization problem needs to meet the following Lagrange function:

$$Ls = U\times\left[fs\left(ks;X\right)-cs\left(w;ks\right)\right]+\lambda s\times gs\left(ks,X,w,\eta\right),\forall S \tag{5}$$

In Eq. 5, λS represents the Lagrange multiplier. The Kuhn-Tucker theorem extends the application of the Lagrange multiplier method to address inequality constraints. It asserts that for a constrained optimization problem to have a feasible solution, specific conditions must be met at that solution in order to be deemed optimal. The Kuhn-Tucker theorem sets forth six fundamental conditions that must be met. First, the problem's objective function should be either maximized or minimized. Second, all constraints, including equality and inequality constraints, must be satisfied. Additionally, the Lagrange multipliers associated with these constraints must be greater than or equal to zero. Moreover, for each constraint, the product of the Lagrange multiplier and the constraint itself should equal zero. Furthermore, the partial derivative of the objective function with respect to each variable must exist at the optimal solution. Lastly, the partial derivatives of the Lagrangian function with respect to all variables must be equal to zero at the optimal solution. These six conditions collectively define the necessary requirements for the application of the Kuhn-Tucker theorem. Based on the optimization condition outlined in the Kuhn-Tucker theorem, the following six conditions are required to hold.

$$\partial Ls*/\partial ks\leq 0$$

$$ks*\times\left(Ls*/ks\right)=0$$

$$ks*\geq 0$$

$$Ls*/\lambda s\geq 0$$

$$\lambda s*\times\left(Ls*/\lambda s\right)=0,$$

$$\lambda s*\geq 0$$

Farmers will choose $s^* = \lim U|s^*=1\geq U|s^*=0$, and vice versa. Furthermore, based on the solution of the optimization problem and the Kuhn-Tucker theorem, FS, CS, and GS are exogenous variables. In Eqs. 6, 7 the decision of whether farmers choose to purchase ASS and the optimal vector of input factors (X, W, η) will be expressed in the following simplified form:

$$S* = r\left(fs, cs, gs, X, w, \eta\right)=r\left(X, w, \eta\right) \tag{6}$$

$$ks* = \varphi\left(fs, cs, gs, X, w, \eta, S*\right)=\varphi(X, w, \eta, S) \tag{7}$$

In Eq. 8, the optimal output function can be simplified as follows:

$$Ys* = fs\left(ks*; X, S*\right) \tag{8}$$

Hence, the agricultural TE can be influenced by the level of ASS adopted by small farmers. This, in turn, can impact the optimal agricultural output.

3 Materials and methods

3.1 Study area

This study was conducted in three provinces located in southern China: Hunan, Jiangxi, and Zhejiang. These provinces are renowned for being the primary rice-producing regions in the country, contributing to approximately 25% of China's total rice production. The selection of these provinces as the study's sample area stemmed from their significant advantages, including vast flat terrain and ample natural water supply, which contribute to comparatively high rice yields per unit of farmland area. Notably, Hunan province stands out with an average rice yield of over 10,000 kg per hectare. Consequently, these provinces were chosen to represent the diversity and productivity of rice cultivation in the research study. For the purpose of this

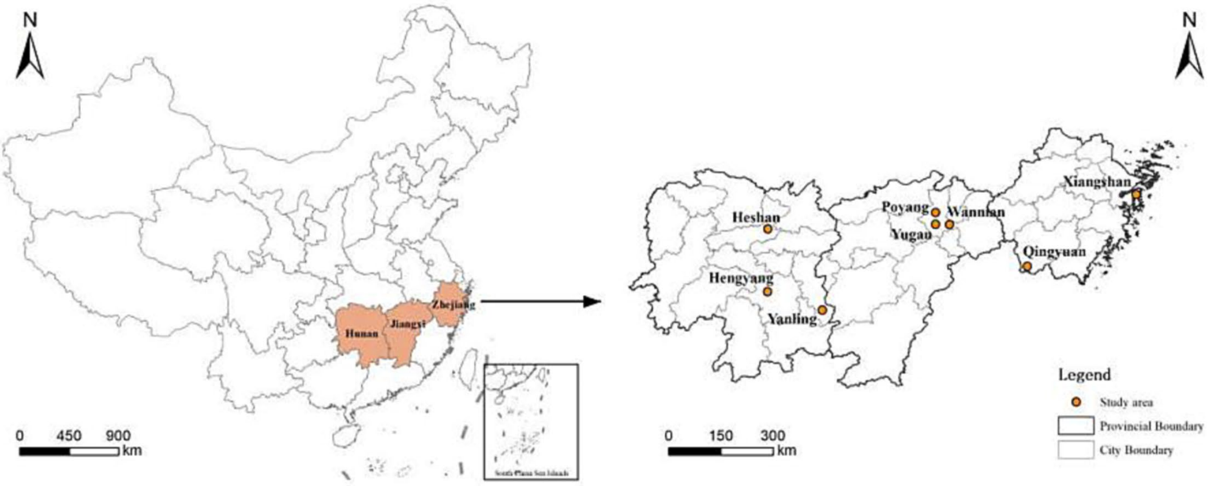

FIGURE 2
Map of the surveyed area. Source: created by the author.

research, a total of eight sample counties were carefully selected from three provinces, taking into consideration factors such as regional development level, geographic position, and agricultural natural resource endowment. In Hunan province, we sampled Hengyang County, Yanling County, and Yiyang County, while in Jiangxi province, our selection included Wannian County, Poyang County, and Yugan County (please refer to Figure 2).

3.2 Household data

During the months of July and August in 2020, data collection took place in the study area. To ensure the representation and validity of the sample households, we employed a multi-stage random sampling method. Initially, 23 households were randomly chosen from each county to establish a diverse and comprehensive sample. Subsequently, we selected a total of 228 households from counties in Hunan province, 334 households from counties in Jiangxi province, and 125 households from counties in Zhejiang province. The selection of households from each county was based on the accessibility of ASS. As a result, a total of 741 households were identified as representative samples for our study. To gather data, we distributed a total of 800 questionnaires among the selected households. After careful evaluation, we found that 725 of these questionnaires met the criteria and could be considered valid samples, indicating an effective response rate of 90.63%. These valid samples formed the foundation for our analysis and findings in this study. The survey conducted for this study has received approval from the Institutional Review Board (IRB), confirming that the study procedures and ethical considerations have been thoroughly reviewed and found to meet the necessary standards for conducting research involving human subjects (household surveys).

The primary focus of this research was to gather information related to ASS, TE, individual characteristics, cultivated land characteristics, and village characteristics as utilized by rice farmers. To ensure effective communication with the target population (as farmers only spoke Chinese), the questionnaires were initially prepared in English and then translated into Chinese. The questionnaire development process involved careful design, pre-investigation, and modification to ensure farmers' full comprehension and willingness to participate in face-to-face interviews. To validate the interview procedure, enumerators were trained and a pre-test was conducted. Face-to-face interviews were then carried out by the enumerators, and the responses were evaluated by the authors. The questionnaire aimed to collect essential data for the study, including key characteristics such as the socio-economic background of smallholder farmers, the adoption of ASS, land management practices, village geographical locations, and other relevant information. The data collection period for this study was conducted from June to August 2020. The data collected pertains to the actual production time of the farmers, which occurred in the year 2019. It is important to note that the surveyed population consisted of smallholder farmers who engaged in rice cultivation and utilized ASS.

3.3 Estimation model

This paper adopts the stochastic frontier approach (SFA) as a methodological tool to evaluate the technical efficiency of agricultural production. The SFA model was first introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), and later further improved by Battese and Coelli (1995). SFA is a statistical technique that is commonly used to estimate the production efficiency of firms in a given industry, including agriculture. It involves decomposing observed output into two components: technical inefficiency and random disturbance. The technical inefficiency component measures the gap between actual production and the maximum possible production level given the available technology. It is influenced by factors such as managerial skills, farm size, input use, and environmental factors that may affect production. On the other hand, the random disturbance component reflects unpredictable factors, such as weather conditions or market fluctuations, that can influence production. SFA has been widely applied in agricultural research to identify factors that affect production efficiency and to provide insights into best management practices for farmers. It allows for the identification of inefficiencies in production processes and provides practical recommendations for improving agricultural productivity. Based on previous research, this study adopts the fundamental structure of the stochastic frontier production function as:

$$\mathrm{Yi} = \mathrm{f}(\mathrm{xi}; \beta)\exp(\mathrm{vi} - \mathrm{ui}) \tag{9}$$

In the above equation with Eq. 9, Yi denotes the actual output, f(X) represents the agricultural production function, Xi represents the input vector of production factors, β represents the parameter to be estimated, Vi represents the measurement error and random interference factor. To obtain the stochastic version for measuring technical efficiency, it is crucial to select the appropriate functional form. In this study, an econometric approach known as the stochastic frontier approach (SFA) is employed. It is recommended to consider multiple alternative models and choose the preferred one based on the likelihood ratio, following the study by Coellis (1996), Lau (1986), Reynes (2017), and Murthy (2002). The SFA is a parametric approach that requires assuming a specific function form beforehand, and the frontier is estimated using the maximum likelihood approach, as described by Coelli T et al. (2005) and Coelli TJ et al. (2005). A crucial decision lies in choosing between the Cobb–Douglas model and the translog model, which are commonly used functional forms in empirical studies on production, including frontier analysis (Lau, 1986). Both the Cobb–Douglas and translog production functions can be accommodated within the SFA framework. To determine the appropriate functional form, it is necessary to test the competence of the Cobb–Douglas model against the less restrictive translog model under the null hypothesis that the Cobb–Douglas form is correct. In the SFA model, the parameters of both the Cobb–Douglas and translog models are estimated using the maximum likelihood approach, and the likelihood ratio values for each model are compared to determine which one is more suitable. The form of a stochastic frontier model using the Cobb–Douglas functional form is given in Eq. 10:

$$\ln Y_{it} = a_0 + \sum_j a_j \, lnX_{itj} + \beta_k lnZ_{it} + V_{it} - U_i \tag{10}$$

The following is the representation of a stochastic frontier model utilizing the translog functional form:

$$\begin{aligned}\ln Y_{it} &= a_0 + \sum_j a_j \, lnX_{itj} + \beta_k lnZ_{it} + \frac{1}{2}\sum_j \sum_l a_{jl} \, lnX_{itj} \\ &+ a_{jl} \, lnX_{itl} + \frac{1}{2}\beta_{kk}\left(lnZ_{it}\right)^2 \\ &+ \sum_j \sum_k \S_{jk} \, lnX_{itj} lnZ_{it} + V_{it} + U_i\end{aligned} \tag{11}$$

In Eq. 11, $\S_{jk} = \S_{kj}$ When U_i is equal to zero and technical efficient farmer is producing logarithm of the output Y_{it}, by utilizing X_{it} and Z_{it} in Eq. 6, the trans log SFA for technical efficient can be specified as:

$$\begin{aligned}\ln Y_{it} &= a_0 + \sum_j a_j \, lnX_{itj} + \beta_k lnZ_{it} \\ &+ \frac{1}{2}\sum_j \sum_l a_{jl} \, lnX_{itj} + a_{jl} \, lnX_{itl} + \frac{1}{2}\beta_{kk}\left(lnZ_{it}\right)^2 \\ &+ \sum_j \sum_k \S_{jk} \, lnX_{itj} lnZ_{it} + V_{it}\end{aligned} \tag{12}$$

In a Eq. 12, technical efficiency detrimental input Z_{it} is replaced by Z_{it} and if the technical efficient farmer is utilizing $X_{it}$and Z_{it}, for producing Y_{it}^F, then the equation becomes:

$$\begin{aligned}\ln Y_{it}^F &= a_0 + \sum_j a_j \, lnX_{itj} + \beta_k lnZ_{it} \\ &+ \frac{1}{2}\sum_j \sum_l a_{jl} \, lnX_{itl} + \frac{1}{2}\beta_{kk}\left(lnZ_{it}\right)^2 \\ &+ \sum_j \sum_k \S_{jk} \, lnX_{itj} lnZ_{it} + V_{it}\end{aligned} \tag{13}$$

where $\ln Y_{it}$, is equal lo $\ln Y_{it}^F$ and lnZ_{it} - lnZ_{it},is equal to the logarithm of stochastic technically efficiency $lnEE_i$. to solve Eqs. 11 and 13 yields:

$$\begin{aligned}&\frac{1}{2}\beta_{kk}[\left(lnZ_{it}\right)^2 - \left(lnZ_{it}\right)^2 \\ &+ \sum_j \sum_k \S_{jk} \, lnX_{itj}\left[\left(lnZ_{it}\right) - \left(lnZ_{it}\right)\right] \\ &+ \beta_k\left[\left(lnZ_{it}\right) - \left(lnZ_{it}\right)\right] + U_i = 0\end{aligned} \tag{14}$$

We can express the above Eq. 14 as Eq. 15:

$$\begin{aligned}&\frac{1}{2}\beta_{kk}\left[\left(lnZ_{it}\right) - \left(lnZ_{it}\right)\right]^2 \\ &+ \left[\beta_k + \sum_j \sum_k \S_{jk} \, lnX_{itj} + \beta_{kk} lnZ_{it}\right] \\ &+ \left(lnZ_{it}\right) - \left(lnZ_{it}\right) + U_i = 0\end{aligned} \tag{15}$$

For solving $lnTE_{it}$ = (lnZ_{it}) - (lnZ_{it}), we can obtain in Eq. 16:

$$\begin{aligned}lnTE_{it} &= [-(\beta_k + \textstyle\sum_j \sum_k \S_{jk} \, lnX_{itj} + \beta_{kk} lnZ_{it}] \\ &\pm\{(\beta_k + \textstyle\sum_j \sum_k \S_{jk} \, lnX_{itj} + \beta_{kk} lnZ_{it})^2 \\ &- 2\beta_{kk} U_i\}^5] / \beta_{kk} = 0\end{aligned} \tag{16}$$

The estimation of parameters related to the adequacy of the frontier model is assessed through the utilization of the maximum likelihood-ratio estimator. A comparison between the Cobb–Douglas and translog models relies on the likelihood ratio statistics, as outlined by Reynes (2017), Murthy (2002), Coelli T et al. (2005), and Coelli TJ et al. (2005), expressed as:

$$\lambda = -2\left\{\ln\left[L\left(H_0\right)\right] - \ln\left[L\left(\left(H_1\right)\right]\right\}\right.$$

The value of A, which represents the likelihood ratio, is determined by In [L (H0)], the logarithmic value of the likelihood ratio of the Cobb–Douglas model with restrictions, assuming that it is the most appropriate model. Meanwhile, *In [L(H1)]* corresponds to the logarithmic value of the likelihood ratio of the translog model without restrictions, assuming that it is the most suitable model for the study. The maximum likelihood ratio is assumed to follow a Chi-square distribution (x_2), as described by Reynes (2017), Murthy (2002), and Coelli et al. (1998).

The estimation of both the suitable SFA model and technical inefficiency involved using the likelihood method. The log likelihood test was utilized to determine the necessity of incorporating the effect of inefficiency. This test enables the assessment of the error variance ratio parameter, known as gamma (Υ), and sigma square (σ^2), expressed as $\sigma^2{}_w = \sigma^2{}_v + \sigma^2{}_u$ and $\Upsilon = \sigma^2{}_u / \sigma^2{}_w$ (Battese and Coelli, 1995). The sigma square value serves as a measure of the data fit within the model, while the gamma value falls within the range of 0 to 1. A value of $\Upsilon = 0$ indicates the presence of noise effect, whereas $\Upsilon = 1$ indicates inefficiency effect. This estimation process entails evaluating the null hypothesis (H_o), which posits that there are no effects of technical inefficiency present in the countries represented by $\gamma = 0$, against the alternative hypothesis (H_a), which suggests that "there exists technical inefficiency in the countries" with $\gamma = 1$.

3.4 Variable descriptions

3.4.1 Explained variable

In this study, the explanatory variable is the TE of rice production conducted by smallholder farmers. The average grain or rice yield per unit of land (mu) is used as a measure to calculate the technical efficiency of the farmers. To accurately assess the technical efficiency, the average yield of two crops of rice is considered when farmers engage in double harvests. This accounts for the variation in productivity resulting from multiple rice cultivation cycles within a single season. By incorporating the average yield from both crops, we obtain a comprehensive understanding of the farmers' technical efficiency in maximizing their output within a given land area.

3.4.2 Independent variable

To assess the level of ASS development in the village where smallholder farmers reside, this study employs the average amount of ASS utilized to produce one season's worth of rice per mu. This indicator offers a more precise evaluation of the local ASS status as compared to availability-based metrics like the presence or absence of local ASS. Furthermore, this study also calculates the ASS level of the various links involved in rice production, including tillage, transplantation, crop protection, and harvesting operations. The independent factors of farmland size, agricultural labor availability, and capital investment are also taken into account.

3.4.3 Control variables

The inclusion of control variables allows us to examine the impact of these variables on both the utilization of ASS and the TE of smallholder farmers. Additionally, it helps in distinguishing between farmers who utilize ASS and those who do not. Drawing upon the rational small-scale peasant economy theory and referring to relevant research findings from (Chen et al., 2022), this study considers several factors as control variables. These factors encompass individual characteristics of farmers (such as age, education level, and physical health of the household head), characteristics of cultivated land (including the degree of fragmentation, leveling, and fertility), and village characteristics (such as the level of local agricultural infrastructure). By including these control variables, we can gain insights into their influence on the demand for ASS among smallholder farmers (Li, 2015). This approach enables us to better understand how these variables interact with the utilization of ASS and contribute to the overall TE of the farmers.

4 Results and discussion

4.1 Results of the descriptive statistics

The Table 1 presents an overview of the variables used in this study and their descriptive statistics. The dependent variable, rice production per mu, indicates that smallholder farmers in the study area produce an average of 621 kg of rice. One important independent variable is the actual expenditure of ASS for rice production per mu, which represents the level of ASS development. The average cost is 266.806 yuan, suggesting that there is potential for improvement in the provision of ASS. Regarding the characteristics of the respondents, the average age is approximately 61.85 years, indicating that elderly farmers play a significant role in rice production and highlighting the significance of ASS in enhancing labor productivity. Furthermore, most respondents have a primary school education, with an average of 3.98 years of education. The table also provides information on the features of the surveyed farmland. The degree of land fragmentation, measured by the number of cultivated land blocks divided by the actual cultivated land area, is relatively high at 1.226. On the other hand, the topography of the land used for rice cultivation tends to be flat, as indicated by a value of 1.858. This suggests that the cultivated land is generally suitable for rice production. In terms of land quality, the fertility level for rice farming is moderately favorable with an average score of 3.310 on a scale of 1 to 5. This indicates that there is room for further enhancing the quality of farmlands. Furthermore, the level of infrastructural development in the studied area is relatively low, as denoted by an average value of 0.357. This implies that the community's characteristics and resources are influenced by the limited state of infrastructure. These descriptive statistics provide a preliminary understanding of the variables involved in the study and set the stage for further analysis to investigate the factors influencing rice production efficiency.

4.2 Results of likelihood ratio test

The LR test, also known as the likelihood ratio test, is a statistical tool used to compare two models and determine which one provides a better fit to the data. In this case, the two models being compared are the model containing only the intercept and the function model utilizing the Stochastic Frontier Approach (SFA). The LR test yielded a result of LR = 17.7 and a p-value of 0.0069. The p-value represents

TABLE 1 A summary of the variables utilized in this study along with their descriptive statistics.

Variables	Definition	Mean	S.D.
Explained variables			
TE of rice production	TE of 2020 rice production season	1242.17	301.18
Independent variables			
ASS level	Actual expenditure of ASS for producing one season of rice per mu (yuan)	266.81	62.41
ASS of tillage	Proportion of households purchasing total ASS of tillage operation	0.78	0.15
ASS transplanting	Proportion of households purchasing ASS of transplanting (%)	0.34	0.19
ASS crop-protection	Proportion of households purchasing ASS of crop-protection (%)	0.19	0.15
ASS of harvest operation	Proportion of households purchasing ASS of harvest operation (%)	0.82	0.18
Cultivated land management scale	Actual cultivated land area (MU)	8.60	7.81
Number of agricultural labor force	Number of household labor force excluding the number of migrant workers	1.61	1.06
Average capital investment per mu	Agricultural expenses such as agricultural materials and ASS (yuan / mu)	577.88	157.27
Control variables			
Individual characteristics			
Age	Actual age of respondents (years)	61.85	9.53
Education level	Education years of respondents (years)	3.98	3.09
Physical health	Years of migrant work of respondents (years)	3.65	1.02
Cultivated land characteristics			
Degree of land fragmentation	Number of cultivated land blocks / actual cultivated land area (block/ mu)	1.226	1.378
Cultivated land levelling	Flat = 1; A little slope = 2; Large slope = 3	1.858	0.801
Cultivated land fertility	1 = very poor; 2 = poor; 3 = General; 4 = better; 5 = very good	3.310	0.868
Village characteristics			
Agricultural infrastructure level	Does the village have high standard farmland construction? Yes = 1, no = 0	0.357	0.480

the probability of obtaining the observed test statistic or a more extreme value under the null hypothesis, which, in this case, is that the model containing only the intercept is a better fit for the data than the function model. Since the p-value is less than the set level of significance (usually 0.05), we can reject the null hypothesis and conclude that the function model fits the data better than the model containing only the intercept. This result indicates that the choice to use the Stochastic Frontier Approach (SFA) in this paper is reasonable. In this study, the Stata 16 software was utilized to run the model.

4.3 Results of stochastic frontier production function estimation

The utilization of stochastic frontier production functions is crucial in predicting the technical efficiencies of individual entities within the industry as a whole. In this section, the necessity of employing a stochastic frontier production function to examine the impact of ASS on TE is tested. This study combines the stochastic frontier production function and the technical inefficiency model using a one-step method. The determinants of the test results of the stochastic frontier production function are presented in Table 2.

The results presented in Table 2 reveal that the technical inefficiency is statistically significant at a significance level of 1%. This indicates that small-scale farmers experience technical inefficiencies in their agricultural production processes. Additionally, the γ value of 0.065 is greater than 0, suggesting that the variation in the composite error term primarily stems from the technical inefficiency component. This finding underscores the necessity of employing a stochastic frontier production function to accurately capture and account for the technical inefficiencies present in the agricultural production of small farmers.

4.4 Estimation of the role of ASS on the whole TE

Table 3 presents the determinants of smallholder farmers' TE in rice production, with ASS introduced as an explanatory variable. The results indicate that the coefficient of ASS is −0.137, and it is statistically significant at a significance level of 1%. This signifies that ASS has a significant and negative impact on the technical inefficiency experienced by smallholder farmers. The observed negative and significant effect of ASS on technical inefficiency suggests that the provision of ASS enhances the TE of rice production carried out by smallholder farmers. The introduction of ASS in the process of rice production for smallholder farmers promotes their overall TE by a magnitude of 0.137. As a result, this finding supports the verification of hypothesis H1. This finding aligns with the research conducted by Chen et al. (2022), who discovered that the provision of ASS plays a

TABLE 2 The estimation results of stochastic frontier production function.

Explanatory variable	Dependent variable (outputs level)	
	Coefficient	S.E.
Land	0.033***	0.012
Labour	−0.002	0.023
Capital	0.042	0.031
Intercept term	7.091***	0.204
λ	3.76	0.044
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.185	
$\gamma = \sigma_u^2 / \sigma_u^2 + \sigma_v^2$	0.065	
LR test of sigma_u	77.44 (p-value:0.000)	

***$p < 0.01$, **$p < 0.05$, *$p < 0.01$.

TABLE 3 The estimation results of the impact of ASS on agricultural TE of smallholder farmers.

Variable	Dependent variable (technical inefficiency)	
	Coefficient	S.E.
ASS	−0.137***	0.037
Age	−0.044	0.053
Cultural level	0.0005	0.003
Physical health	−0.052**	0.024
Degree of land fragmentation	0.001	0.011
Cultivated land levelling	−0.070***	0.020
Cultivated land fertility	−0.010	0.028
Agricultural infrastructure level	−0.058***	0.019
Constant term	1.389***	0.311

***$p < 0.01$, **$p < 0.05$, *$p < 0.01$.

substantial role in agricultural scale development, increasing land productivity, and ultimately enhancing agricultural technical efficiency. Furthermore, the findings of Hao et al. (2020) and Qian et al. (2020) also support our results, indicating that ASS contribute to the improvement of TE in smallholder farmers' agricultural production by inducing division of labor and increasing the application of technological inputs. The estimation results in Table 3 provide evidence of the positive impact of ASS on the TE of agricultural production among smallholder farmers.

Among the control variables, the health status of smallholder farmers, cultivated land levelling, and agricultural infrastructure level have a significant negative impact on the agricultural technology inefficiency of small farmers. This suggests that these three variables play a crucial role in improving the agricultural technology efficiency of smallholder farmers. The negative impact of the health status of smallholder farmers implies that better health conditions positively contribute to their agricultural technology efficiency. Similarly, the significance of cultivated land levelling indicates that a more even and well-prepared land surface helps enhance agricultural technology efficiency. Additionally, the agricultural infrastructure level, which likely includes factors such as access to irrigation systems or transportation networks, also has a significant negative influence on technology inefficiency, suggesting that improved infrastructure facilitates more efficient agricultural practices.

The mentioned findings are consistent with the research conducted by Chen et al. (2022), which revealed that ASS provide a higher incentive for the older generation of farmers to adopt arable land quality protection. This implies that ASS not only directly impact technology efficiency but also indirectly influence it by encouraging the adoption of sustainable farming practices among older farmers. These results highlight the importance of considering various factors, such as health status, land preparation, and agricultural infrastructure, in improving the technology efficiency of smallholder farmers, and further emphasize the role of ASS in promoting sustainable agricultural practices.

4.5 Estimation of the impact of the different links of ASS on TE of smallholder farmers

This study focuses on four main agricultural links: tillage, transplanting, crop-protection, and harvest operation. The impact of ASS on the TE of smallholder farmers' rice production in these specific agricultural links is examined.

Table 4 presents the determinants of the impact of ASS on the TE of rice production in each agricultural link, and the results show heterogeneity across the links. The coefficient of ASS for transplanting is negative and statistically significant at a significance level of 1%, indicating that ASS related to transplanting reduces the technical inefficiency experienced by smallholder farmers in this particular agricultural link. Similarly, the coefficient of ASS for crop-protection is negative and significant at a significance level of 5%, suggesting that ASS in crop-protection contributes to decreasing the technical inefficiency of rice production by smallholder farmers. Additionally, the coefficient of ASS for harvest operation is negative and significant at a significance level of 5%, implying that ASS in harvest operation also helps reduce technical inefficiency in rice production among smallholder farmers. These findings indicate that the provision of ASS in these three specific agricultural links (transplanting, crop-protection, and harvest operation) is beneficial for improving the overall TE of smallholder farmers in rice production. Thus, these findings support the verification of hypothesis H1, which presumably states that ASS positively impacts the TE of smallholder farmers. The analysis reveals that the impact of ASS on TE varies across different agricultural links. The provision of ASS in transplanting, crop-protection, and harvest operation is found to significantly decrease technical inefficiency and contribute to enhanced TE in rice production conducted by smallholder farmers.

The analysis indicates that ASS related to harvest operation has a greater impact on TE (with a coefficient of 0.080) than ASS in transplant operation (0.054) and crop-protection (0.027). This difference in impact can be explained by the degree of standardization and mechanization of the respective production links. Harvest operation involves a high degree of standardization and

TABLE 4 Estimation of the impact of different links of ASS on TE.

Variable	Dependent variable: Technical inefficiency item							
	Coefficient	S.D.	Coefficient	S.D.	Coefficient	S.D.	Coefficient	S.D.
Tillage	−0.045	0.044	–	–	–	–	–	–
Transplanting	–	–	−0.054***	0.013	–	–	–	–
Crop protection	–	–	–	–	−0.027**	0.011	–	–
Harvesting operation	–	–	–	–	–	–	−0.080**	0.035
Age	−0.042	0.054	−0.052	0.053	−0.018	0.057	−0.050	0.053
Education level	−0.001	0.003	0.001	0.003	−0.001	0.003	−0.0004	0.003
Physical health	−0.056**	0.025	−0.052**	0.024	−0.091***	0.026	−0.058**	0.025
Degree of land fragmentation	0.011	0.011	0.001	0.011	−0.004	0.012	0.009	0.011
Cultivated land levelling	−0.074***	0.020	−0.072***	0.019	−0.085***	0.021	−0.076***	0.020
Cultivated land fertility	−0.013	0.029	−0.009	0.028	−0.037	0.032	−0.009	0.029
Agricultural infrastructure level	−0.046**	0.020	−0.058***	0.018	−0.058***	0.020	−0.055***	0.019
Constant term	0.623***	0.239	0.598**	0.239	0.563**	0.256	0.648***	0.235

***$p < 0.01$, **$p < 0.05$, *$p < 0.01$.

mechanization, which reduces the influence of human factors compared to other agricultural links. Mechanized harvesting services, for example, can significantly reduce grain wastage, increase grain yield, and enhance agricultural TE.

In contrast, the coefficient of ASS related to tillage operation is insignificant, implying that the impact of ASS on TE is unclear. The result revealed two possible reasons for this finding. Firstly, the impact of ASS in tillage operation may be affected by land fragmentation, which also impedes the positive impact of ASS on agricultural TE. Secondly, the low quality of cultivated land may suppress the role of ASS in tillage operation in improving rice production TE. Therefore, the quality of cultivated land needs to be considered in further examining the relationship between ASS and TE. The study reveals that the impact of ASS on TE varies across different agricultural links, with ASS related to harvest operation having the greatest positive effect. However, factors such as land fragmentation and the quality of cultivated land can potentially affect the impact of ASS on TE.

5 Conclusion and policy implications

The findings of this study highlight the significant impact of ASS on the TE of smallholder rice farmers. The empirical analysis, based on data from 741 smallholder farmers in three provinces, reveals that ASS improves the overall TE of rice production. However, the effect of ASS varies across different stages of agricultural production. Specifically, ASS has a positive and significant impact on the TE of transplanting, crop-protection, and harvest operations. This underscores the importance of enhancing these specific areas of support to further improve smallholder farmers' TE. On the other hand, the study finds no significant impact of ASS on the TE of tillage operations, suggesting a need for further investigation and potential adjustments in the delivery of support services related to this stage.

Based on these findings, several policy recommendations can be derived. Firstly, it is crucial to align the provision of ASS with the specific needs and demands of smallholder farmers. This can be achieved by engaging farmers and ensuring that the services provided are tailored to their requirements. Building trust and confidence in ASS entities is essential, as farmers may be hesitant to adopt new services due to uncertainty about the potential consequences for their rice production. Secondly, addressing the cost barrier is crucial in promoting the uptake of support services. Implementing incentives for both service providers and smallholder farmers can help alleviate financial burdens and increase accessibility to quality services. This dual approach will not only enhance farmers' capacity to afford services but also contribute to the development and availability of support services at the local level. Thirdly, a robust management system for ASS should be established, guided by appropriate legal procedures, scientific standards, and centralized monitoring systems. Ensuring quality service delivery is vital for sustainable agricultural TE development. By setting clear guidelines and enforcing accountability, the reliability and effectiveness of support services can be improved.

This study contributes to the theoretical understanding of agricultural efficiency and the role of socialized services in enhancing technical efficiency. By investigating the influence of ASS on smallholder rice farmers' technical efficiency, the study provides insights into the relationship between access to services, adoption of modern production techniques, and overall productivity. The findings contribute to the existing literature on agricultural development, rural livelihoods, and food security by highlighting the importance of targeted interventions and collective action in improving agricultural efficiency. The empirical findings of this study provide concrete evidence of the significant impact of ASS on the technical efficiency of smallholder rice farmers in southern China. By employing stochastic frontier analysis and collecting data from three provinces, the study presents robust empirical evidence that supports the positive relationship between participation in socialized services and enhanced technical efficiency. The study's methodology and results contribute to the empirical understanding of the factors influencing agricultural productivity and offer a reference point for future empirical research in similar contexts.

The practical implications of this study are significant for policymakers, agricultural organizations, and smallholder farmers themselves. The findings suggest that promoting access to ASS can lead to improved technical efficiency, sustainable farming practices, and increased access to credit, financing, and market information. Policymakers can utilize these insights to design targeted interventions that address the challenges faced by smallholder farmers and promote efficient agricultural practices. Agricultural organizations can use this knowledge to develop and implement programs that enhance smallholders' access to services, resources, and knowledge. For smallholder farmers, the study highlights the potential benefits of participating in socialized services, empowering them to enhance their productivity, support their livelihoods, and contribute to overall food security in the region.

While this study provides valuable insights into the relationship between ASS and TE for smallholder rice farmers, there are some limitations that should be addressed in future research. Firstly, expanding the analysis to include other crop types would provide a more comprehensive understanding of the impact of ASS across different agricultural contexts. Additionally, incorporating longitudinal data to capture temporal trends would enhance the robustness of the findings. Lastly, conducting similar studies at a national level would contribute significantly to evidence-based decision-making among policymakers. In conclusion, this study underscores the importance of strengthening ASS to enhance the technical efficiency of smallholder rice farmers. The policy recommendations emphasize the need to align services with farmers' demands, address cost barriers, and establish a robust management system. By implementing these measures, policymakers can effectively support smallholder farmers and promote sustainable agricultural development.

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

BC: Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. FS: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. AM: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Writing – original draft, Writing – review & editing. GB: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. RZ: Conceptualization, Data curation, Investigation, Writing – review & editing.

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Conflict of interest

The authors declare 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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