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Effect of agricultural socialisation services on green grain production efficiency: Evidence from Jiangsu Province, China

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Abstract: In this study, we examine the effect of Agricultural Socialisation Services (ASS) on green grain production efficiency in Jiangsu Province, China, by using data from the China Land Economy Survey. We used the generalised random forests model in this research to address potential issues of farming household self-selection into ASS and unobserved heterogeneity in treatment effects. The results show that participation in ASS significantly improves green production efficiency, particularly for small-scale farmers. Efficiency gains are most pronounced in critical agronomic operations such as pest control, seeding and planting, whereas smaller efficiency effects are observed in plowing, harvesting and straw treatment. The findings suggest that targeted expansion of ASS could substantially enhance sustainable farming practices, especially for resource-constrained farms. This study provides important policy insights for promoting agricultural sustainability through improved access to and delivery of agricultural services, contributing to more efficient and ecofriendly grain production.

Keywords: generalised random forests; small-scale farmers; sustainable farming practises

The rapid urbanisation driven by the reform and opening up of China's economy has witnessed a significant influx of rural labour into urban areas. To compensate for the labour shortages, rural households have resorted to extensive consumption of production resources. This problem is leading to challenges in grain production such as high costs, energy consumption and inefficiency. This trend has exacerbated issues like escalating carbon emissions and unsustainable land use (Du et al. 2024), posing a growing threat to the security of China's grain production and the modernisation of its agricultural sector (Liu et al. 2020).

Agricultural Socialisation Services (ASS) involve contracting out various stages of farming to larger producers, professional service teams or agricultural cooperatives. This process encompasses a range of services, including pre-production technical training, ongoing production support, and post-harvest management. These services are customised to meet the unique needs of individual farmers, with the goal of fostering sustainable and efficient agricultural practices (Yao et al. 2024; Liu et al. 2022; Cai et al. 2024). ASS are seen as crucial for smallholder farmers to gain access to modern agricultural technologies and practices and as leading to high expectations in terms of address-

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ing the division of agricultural labour and achieving cost-effectiveness (Chen et al. 2022b; Liu et al. 2020). ASS aim to mitigate unnecessary waste of resources, reducing carbon emissions and enhancing sustainable land management. Eventually, farmers will be able to connect with the modernisation of agriculture.

However, the role of ASS in advancing smallholder farmers' production modernisation remains contentious. Results from some studies suggest that ASS can drive the modernisation of smallholder farming. Initially, these services can be a substitute for labour, leading to enhanced production efficiency (Kannan 2013; Ugwoke 2013). ASS facilitate mechanisation, mitigating efficiency losses due to an aging workforce and enhancing labour productivity (Kannan 2013; Klepacka et al. 2019). According to results from some studies, ASS can facilitate the diffusion and spillover of agricultural production technologies, reducing production costs through extensive service provision, thus promoting the modernisation of smallholder farming (Klepacka et al. 2018; Wang and Han 2020; Chen et al. 2022b). ASS have significantly boosted household incomes (Lyne et al. 2018; Mi et al. 2020) and reduced production costs (Tang et al. 2018).

However, other research results indicate that the transaction costs of ASS are high (Ma 2018; Mumtaz 2018), leading to the emergence of 'leapfrogging' by larger farms (Xia et al. 2020), and issues of loosely connected interests (Chen 2020), hindering the modernisation of smallholder farming. ASS can negatively affect agricultural efficiency because of high costs, low standardisation and production-specific challenges. Outsourcing in pest control has been shown to reduce technical efficiency (Sun et al. 2018). Moral hazards and opportunism in service provision, stemming from the natural characteristics and unique aspects of agricultural production, can compromise service quality and farmer satisfaction (Taylor and Bhasme 2018; Lu et al. 2021).

The limitations of much current research are manifold. Firstly, the understanding of agricultural modernisation is often incomplete, frequently overlooking the inclusion of costs, benefits and carbon emissions within the scope of analysis. Secondly, investigators in the existing research have recognised that the differentiation among farmers may affect the effectiveness of ASS, but their findings have not led to a unified view on how the significant differences among rural households in China affect the how well these services function, and such research has not been empirically tested. Lastly, the choice of research methodology is often problematic, with many studies relying on traditional models like ordinary least squares (OLS), which may not adequately address sample self-selection bias. This reliance on OLS and similar models can lead to findings that are less robust and potentially biased.

Comparing previous studies in which the role of ASS is discussed led to innovation in our research in several aspects. Firstly, we analysed the effect of ASS on green production efficiency. Efficiency here encompasses both the traditional conversion of inputs to crop yields and the environmental effect, notably pollution, as a critical indicator of grain quality. Secondly, in this research, we delved into the phenomenon of differentiation within the farming community. The significant increase in the frequency of land transfers among agricultural households has led to disparities in development among farmers. Against this backdrop, we conducted an empirical examination of the effect of such disparities on the effectiveness of ASS. Thirdly, in term of research methodology in this study, we used a generalised random forests (GRF) model to infer the relationship between the purchase of ASS with green production efficiency causally. In this study, we addressed endogeneity from self-selection, often neglected in prior research. Instead of the common OLS or propensity score matching models, which have limitations in variable handling and feature selection, we used advanced machine learning methods (Dey et al. 2023) to capture individual variability and overcome dimensionality issues, ensuring robust findings.

In summary, on the basis of the literature review and the problem statement, we sought in this study to answer the following questions: What is the effect of ASS on the efficiency of green grain production? How do the heterogeneous characteristics of households influence the returns to ASS? Through which channels do ASS affect the efficiency of green grain production?

Theoretical concept

Hayami's (1971) theory of induced technological change suggests that changes in agricultural resource availability lead to shifts in relative prices. These shifts drive the development of new innovations designed to conserve increasingly scarce resources. With the significant depletion of rural labour, labour itself has become scarce. This scarcity has spurred a search for alternative resources to replace labour (Zhao et al. 2021).

ASS have become a substitute for various factors of agricultural production (Yao et al. 2024). The organisation of ASS consists mainly of agricultural companies engaged in agricultural production, governmental

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organisations and, to a lesser extent, farmers operating on a large scale. ASS organisations can help farmers in production by providing services such as professional technicians, modern equipment and tools (Chen et al. 2023). Such services have the potential to replace labour and provide farmers with advanced production technologies, thereby enhancing agricultural production processes.

There are two main effects of ASS on green production. Firstly, ASS enhance farmers' technical abilities, promoting the adoption of new technologies and the cultivation of ecofriendly production practices (Dinar et al. 2007; Dong and Mu 2019). Secondly, ASS organisations, by merging farmers' land, boost the efficiency of large-scale farming operations. This consolidation not only improves the performance of agricultural machinery but also cuts down on avoidable carbon emissions (Chen et al. 2022a).

These effects lead to the formulation of the first hypothesis:

H_1: ASS have the potential to enhance the efficiency of farmers' ecofriendly grain production.

Furthermore, ASS produce distributional effects. The aforementioned discussion assumes homogeneity among farmers, which fails to account for the prevailing variability due to land transfer and other factors. Present-day farmers are substantially diverse in their resource endowments, which leads to disparate returns on investment in ASS among different demographic groups (Cao et al. 2020). In light of these considerations, the research findings suggest that an underlying distributional effect emerges regarding these services. This effect pertains to the dispersion of benefits derived from ASS among distinct farm households. Some reap greater advantages, others lesser, and some may not benefit at al. Therefore, examining the varied effects of ASS on different groups can yield a fuller understanding of their overall effect on grain production efficiency. In summary, we propose the following hypothes

H_2: A distributional effect is evident regarding ASS, with smallholder farmers likely positioned to accrue greater returns with such services.

METHODS

Three-stage super-efficient slacks-based measure model

Traditional data envelopment analysis (DEA) does not account for the effect of external environmental differences on production efficiency, leading to biased efficiency measurements and an inability to consider non-desired outputs. In radial DEA models, inefficiency is measured solely by proportional input and output adjustments. For inefficient decision-making units (DMUs), the gap from the strong efficiency target includes slacks not captured in efficiency scores. To address this, Tone (2001) introduced the slacks-based measure (SBM) model. To enhance discrimination among effective DMUs, Tone (2002) introduced an input-oriented super-efficiency SBM model for more nuanced analysis. In addition, considering the significant environmental differences among various plots of land, the three-stage super-efficient SBM can eliminate the interference of external environments in the measurement of actual green production efficiency for grains. Therefore, in this study, we opted for the three-stage super-efficient SBM model to measure the efficiency of green grain production accurately, given that this model addresses the shortcomings of the other methods by considering external factors and non-desired outputs.

In stage one, we used an input-focussed super-efficient SBM model to assess the green production efficiency of grain across all DMUs. In the initial phase, we used an input-oriented super-efficiency SBM model under constant returns to scale to circumvent the traditional DEA model's shortcomings in slacks handling, radial bias and its consequences. This model enables the calculation of the DMUs' efficiency in managing rural domestic sewage, as depicted in Equation (1).

$$min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}}}{1 + \frac{1}{s}\sum_{j=1}^{s}\frac{S_j^+}{y_{j0}}}$$
$$s.t.\begin{cases} x_0 = X\lambda + s^- \\ y_0 = X\lambda - s^+ \\ \lambda \geq 0.s^- \geq 0.s^+ \geq 0 \end{cases} \tag{1}$$

where: ρ – efficiency; m and s – counts of input and output indicators; s^+ and s^- – input and output slacks; x_0 and y_0 – input-output vectors of the x_{i0} and y_{j0}, which are the i-th and j-th elements of x_{i0} and y_{j0}; X and Y – input-output matrices for all DMUs; and λ – vector of weights.

With $s^- = 0$ and $s^+ = 0$ implying no input-output slacks, DUM(x_0, y_0) is efficient $\rho^* = 1$. To enhance discrimination among efficient DMUs, Tone (2002) introduced an input-oriented super-efficiency SBM model, as detailed in Equation (2).

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$$\delta_I^* = \frac{1}{m}\sum_{i=1}^{m}\bar{x}_i / x_{i0}$$
$$s.t.\begin{cases} \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j \\ \bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j x_j \\ \bar{x} \geq x_0, \bar{y} = y_0, \lambda \geq 0 \end{cases} \tag{2}$$

where: x and y – input and output vectors in the production possibility set; δ^* – super-efficiency SBM model's efficiency score, with all other parameters retaining their definitions from Equation (1).

We categorised outputs as desired grain yield (Chen 2020) and undesired carbon emissions (Liu et al. 2022). Inputs comprise the land (Cai 2024), labour (Liu and Wu 2022), fertilisers (Tang et al. 2018) and pesticides (He et al. 2021) used in grain production.

In the second stage, we used the stochastic frontier analysis regression to examine the link between these environmental variables and the random error term identified in the first stage (Fried et al. 2002). This analysis allowed us to adjust for input variables, neutralising the effects of external factors and random disturbances. Green grain production efficiency is influenced by factors beyond production inputs, such as natural disasters and soil fertility, which are resistant to human intervention yet have serious effects. In this study, we incorporated disaster frequency (Yao et al. 2024), soil fertility (He et al. 2021) and soil type (Lu et al. 2021) as environmental variables to control for the effects of natural conditions on efficiency.

The third stage revisits the super-efficient SBM model, now with adjusted inputs and outputs. This refined approach allowed us to re-evaluate the green grain production efficiency of individual farmers. The resulting efficiency values provide a more accurate and comparable measure of farmers' green production performance at a similar operational level.

GRF model

Traditional methods for inferring causality rely on linear modelling and propensity score matching, focussing on the average treatment effect (ATE) in overall sample data. However, ATE, as an average, might mask individual heterogeneity due to peak-fill-value averaging, obscuring the variability in how individual samples respond to treatments.

Athey et al. (2019) proposes the GRF approach in an attempt to address this problem. This method builds model trees by randomly sampling covariates with replacement, matching the logic of analysis to estimate individual treatment effects. It helps researchers analyse what drives treatment effect heterogeneity and shows the empirical distribution of these effects. It combines statistical theory with machine learning algorithms, optimising confidence intervals and handling complex causal inference problems.

The GRF model entails the initial computation of the conditional mean treatment effect for each individual. The specific formula for the GRF model is as follows:

$$\hat{\tau} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{m}^{(-i)}\left(X_i\right)\right)\left(W_i - \widehat{e^{(-i)}}\left(X_i\right)\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(W_i - \widehat{e^{(-i)}}\left(X_i\right)\right)^2} \tag{3}$$

where: $e(X_i)$ – propensity score representing the probability that an individual receives the treatment at i given the covariate X_i; $m(X_i)$ – predicted value of Y_i (Y_i in this study is the green grain production efficiency) given X_i.

In estimating the conditional mean treatment effect via a GRF model using Equation (1), Athey et al. (2019) notes that $W_i - e^{(-i)}(X_i)$ corresponds to the orthogonalisation estimator, which is the equivalent of removing the effect of X_i from W_i to obtain a consistent estimate of the conditional mean treatment effect in a regression equivalent to the traditional instrumental variables approach in econometric modelling (Liu 2020).

Athey et al. (2019) used the GRF model approach to obtain an estimate of the average treatment effect (ATE) of the GRF model by incorporating the random forest model adaptation kernel function. Revise Equation (3) to the Equation (4):

$$\hat{t}(x) = \frac{\frac{1}{n}\sum_{i=1}^{n}\alpha_i(x)[(Y_i - \hat{m}^{(-1)}(x_i))][w_i - \hat{e}^{(-i)}(x_i)]}{\frac{1}{n}\sum_{i=1}^{n}\alpha_i(x)[(w_i - \hat{e}^{(-i)}(x_i))]} \tag{4}$$

$$\hat{\sigma} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{\tau}_i - \hat{\tau})^2} \tag{5}$$

Equation (4) represents the estimation result of the GRF model for the conditional ATE. We used Athey's (2019) honest method to split data – half for building a random forest, half for estimating the ATE – ensuring reliable results. After we obtained a stable estimate

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of the ATE, Equation (5) gives us its standard deviation, which we used to build the confidence interval for the effect in causal analysis.

Data

The dataset we used in this investigation originates from the China Land Economic Survey spanning the years 2020 to 2022 (Nanjing Agricultural University 2020–2022). In this study, we primarily harnessed data from these three years to explore the influence of agricultural technology services on the efficiency of ecofriendly grain production. The dataset encompassed a total of 2 279 observations, comprising 637 cases in the control cohort and 1 642 cases within the treatment cohort. We excluded samples featuring the largest plot allocated for non-grain cultivation and those with missing data from the analysis.

The dependent variable is agricultural green production efficiency. Drawing on input-output theory, we computed the efficiency of ecofriendly grain production across each plot by using the three-stage SBM model. The green grain production efficiency evaluation index system encompassed two key components: input and output indicators. Accurately gauging green grain production efficiency required the chosen indicators to relate closely to grain production while excluding environmental effect factors. Table 1 presents the details of these specific indicators.

ASS are the core explanatory variable. We deconstructed the grain production process into six distinct stages: ploughing, seedling raising, planting, pest control, harvesting and straw return to the field. For each stage, we queried farmers on their use of ASS (coded as 0 for no and 1 for yes). In this study, any instance of engaging

Table 1. Descriptive statistics of inputs and output indicators for measuring green grain production efficiency using the three-stage super-efficient SBM model

Variable	Variable name	Description of variable	Average value	Standard deviation	Minimum value	Maximum value	Frequencies (percentage of farmers)
Input indicators	land input	area of the plot (ha)	9.38	52.15	0.10	500.00	–
	labour input	number of labor invested in the plot (working hours)	40.82	73.45	0.10	720.00	–
	fertiliser inputs	fertiliser input cost (EUR)	25.99	10.08	5.38	64.10	–
	pesticide inputs	pesticide inputs cost (EUR)	13.09	7.18	0.00	64.87	–
	capital investment	cost of various other inputs to the plot (EUR)	3 991.98	4 334.77	0.00	1 333 758.91	–
	situation of disasters	number of disasters (times)	0.60	1.09	0	4	–
Environmental variables	soil type	1 = sandy 2 = loam 3 = clay	2.44	0.89	1	3	1: 21.85% 2: 20.53% 3: 57.62%
	fertility (of soil)	1 = poor 2 = fair 3 = good	2.43	0.62	1	3	1: 7.13% 2: 42.67% 3: 50.20%
Output indicators	rice output	rice production (t)	10.57	61.08	0.001	840.00	–
	carbon footprint	carbon emissions (t)	5.62	56.30	0.002	200.97	–

Source: Author's elaboration

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ASS in at least one stage warranted assignment of a value of 1, and we marked the absence of such engagement across all stages as 0. To gauge the influence of farmers' involvement in agricultural socialisation on green production efficiency, we measured their participation level by tallying the variety of ASS each farmer used.

Furthermore, the random forest model incorporates control variables from three primary dimensions. Firstly, we included business characteristics to manage the stability of land rights and land fragmentation within the sample. Secondly, we factored in personal characteristics such as gender, cultural background and health status. Lastly, we controlled for village characteristics encompassing aspects such as location, economic conditions, transportation infrastructure and per capita income. Analysis using a grouping t-test on the control variables revealed discernible variations in mean values between the treatment and control groups, hinting at potential self-selection biases concerning the sampling of farmers engaging with ASS.

For a moderating variable in this study, we addressed the significant diversity among farmers by examining the areas of grain production and the degree of land fragmentation. Our goal was to determine whether there was a distributional effect from ASS.

The classification of current land management sizes lacks a rigourous theoretical foundation, typically being based on the area of arable land. In this study, we adopted the categorisation methods from the research of Zhu (2011) and Hu et al. (2022), and we classified farmers into three size groups on the basis of their landholding data: small (fewer than 5 acres), medium (5 to 50 acres) and large (more than 50 acres). For the degree of land consolidation, we referred to Tian et al. (2014)and calculated it by dividing the total land area by the number of plots. A ratio of 1 or higher indicates a high degree of land consolidation, and a ratio lower than 1 suggests a low degree of land consolidation.

RESULTS

GRF results

By leveraging GRF, we computed a consistent estimation of the ATE of respondents, factoring in the respondents' nuanced propensity scores.

Initially, we harnessed the control variables for the identification process within the realm of GRF methodology. Subsequently, we meticulously excluded variables exhibiting an importance level lower than 0.05 to refine the model's precision by eliminating those with feeble explanatory power toward the explained variables. After this curation, we meticulously executed the estimation through GRF. Illustrated in Table 3, the trajectory of the ATE of ASS on the efficiency of green grain production persistently hovers at approximately 0.200 with the augmentation of decision trees.

Table 3 vividly portrays the substantial and affirmative effect of ASS on the efficiency of green grain production. Involvement in ASS can boost green production efficiency by an average of 20%. This phenomenon can be attributed to several factors. Primarily, these services elevate the agricultural technological acumen of farmers, fostering an environment in which farmers enhance their adeptness in managing cutting-edge agricultural practices and judiciously allocate agricultural resources. By averting scenarios in which inadequate agricultural proficiency leads to superfluous resource input and subsequent waste or pollution, the enhancement of grain green production efficiency is realised. Moreover, the labour-replacement function of ASS serves to mitigate labour shortages among farmers, thereby averting inefficiencies stemming from resource overinvestment or compromised productivity due to labour scarcities which, in turn, reinforces the efficiency of green grain production. Consequently, hypothesis H_1 stands validated at this juncture.

Table 4 illustrates that increasing participation in ASS engagement markedly enhanced the green production efficiency of cereals among farmers, yielding an approximate return of 4.3%. This finding reaffirms the substantial effect of these services on the efficiency of green cereal production.

Table 5 illustrates the positive effects of purchasing ASS on grain green production efficiency across various segments. Each of the six segments significantly boosted efficiency. The enhancement of grain green production efficiency was the most pronounced for pest control, followed by seedlings and then planting. Lastly, we considered plowing, harvesting and straw return to the field. Each of these stages significantly boosted grain green production efficiency, further validating the reliability of the findings.

Resource allocation heterogeneity

Figure 1 illustrates the distribution of estimated individual treatment effects of ASS on grain green production efficiency. The range of treatment effect estimates extends from –0.1 to 0.5, indicating that there are considerable differences in the effect of ASS on grain green production efficiency across individuals.

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Table 2. Descriptive statistics of variables used in Generalised Random Forest model for assessing green grain production efficiency

Variable	Variable name	Description	SD	Mean	Min	Max	Frequencies (percentage of farmers)
Explanatory variable	efficiency of green grain production	measured by three-stage SBM	0.36	0.80	0	2	—
Core explanatory variable	ASS	0 = no 1 = yes	0.45	0.72	0	1	0: 27.90% 1: 72.10%
	ASS engagement	seedling; plowing; planting; pest control; harvesting; straw treatment – the study divides agricultural socialisation services into the above six segments	1.89	2.29	0	6	0: 27.90% 1: 9.89% 2: 15.36% 3: 19.96% 4: 12.47% 5: 8.00% 6: 6.42%
	stability of land rights	1 = unspecified duration of land management; 2 = land operation for a definite period of less than 5 years; 3= land management for a definite period of 5 to 10 years; 4 = land operation with a definite duration > 10 years; 5= contracted land	1.13	4.45	1	5	1: 5.56% 2: 4.78% 3: 4.22% 4: 9.65% 5: 75.80%
Personal characteristic	gender	0 = female 1 = male	0.35	0.86	0	1	0: 14.00%, 1: 86.00%
	cultures	1 = elementary school or below 2 = junior high school 3 = senior high school 4 = college 5 = bachelor's degree or above	0.90	2.72	1	5	1: 9.30% 2: 28.38% 3: 45.91% 4: 13.87% 5: 2.54%
	health	1 = unable to work 2 = poor 3 = fair 4 = good 5 = excellent	1.02	4.04	1	5	1: 1.08% 2: 9.78% 3: 14.47% 4: 32.95% 5: 41.73%
Village characteristics	geographical position	distance to county, hospital, bank entropy value gained	0.19	0.77	0.08	1.00	—
	economics	0 = economically weak villages 1 = non-economically weak villages	0.35	0.14	0	1	0: 27.90% 1: 72.10%
Moderate variable	scale of household arabl land operations	1 = small-scale (less than 5 acres) 2 = medium-scale (5 to 50 acres) 3 = large-scale (more than 50 acres)	0.80	1.78	1	3	1: 45.33% 2: 30.72% 3: 23.95%
		0 = low 1 = high	0.49	0.41	0	1	0: 58.36% 1: 41.64%

ASS – Agricultural Socialisation Services; SBM – slack based measure
Source: Author's elaboration

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Table 3. Estimated average treatment effect of Agricultural Socialisation Services on green grain production efficiency using the Generalised Random Forest model

Variable name	Green grain production efficiency				
	number of trees	average treatment effect	standard error	T-value	confidence interval (99%)
ASS	500	0.202***	0.019	10.631	(0.153; 0.251)
	1 000	0.203***	0.019	10.684	(0.155; 0.251)
	1 500	0.202***	0.018	11.284	(0.156; 0.248)
	2 000	0.201***	0.018	11.292	(0.154; 0.248)

*, **, ***significance at the 10, 5 and 1% levels, respectively, with standard errors given in parentheses

Source: Author's elaboration

Table 4. Estimated average treatment effect of Agricultural Socialisation Services Engagement on green grain production efficiency using the Generalised Random Forest model

Variable name	Green grain production efficiency				
	number of trees	average treatment effect	standard error	T-value	confidence interval (99%)
Agricultural Socialisation Services engagement	500	0.042***	0.004	10.146	(0.030; 0.054)
	1 000	0.043***	0.004	9.976	(0.032; 0.054)
	1 500	0.044***	0.005	9.256	(0.030; 0.054)
	2 000	0.044***	0.006	7.857	(0.030; 0.058)

*, **, ***significance at the 10%, 5%, and 1% levels, respectively, with standard errors given in parentheses
Source: Author's elaboration

Table 5. Impact of different segments of different ASS on graqin green production efficiency

Variable name		Average treatment effect	Standard error	T-value	Confidence interval (99%)	Number of trees
Different segments of different Agricultural Socialisation Services	seeding	0.256***	0.042	6.095	(0.199; 0.313)	2 000
	plowing	0.199***	0.021	9.476	(0.146; 0.252)	
	planting	0.230***	0.023	10.000	(0.171; 0.289)	
	pest control	0.268***	0.023	11.652	(0.209; 0.327)	
	harvesting	0.186***	0.020	9.300	(0.133; 0.239)	
	straw treatment	0.193***	0.021	9.190	(0.138; 0.248)	

*, **, ***significance at the 10%, 5%, and 1% levels, respectively, with standard errors given in parentheses; ASS - Agricultural Socialisation Services
Source: Author's elaboration

Table 6 demonstrates that the coefficients of the between-group differences were all significantly positive, indicating that there is a notable degree of heterogeneity in the effect of agricultural technology services on the efficiency of green grain production.

Investigators in previous studies have established that there is considerable heterogeneity among farmers. Further examination of various studies reveals that this heterogeneity is primarily due to inequalities in resource endowments. These resource endowments include scale of household arable land operations (Zhu 2011) and the degree of land consolidation (Liu and Wu 2022).

The findings depicted in Table 7 reveal a notable disparity in the yield from ASS across households with varying characteristics. Farmers overseeing smaller-scale land operations had greater benefits from ASS. Farmers with a high degree of land consolidation also

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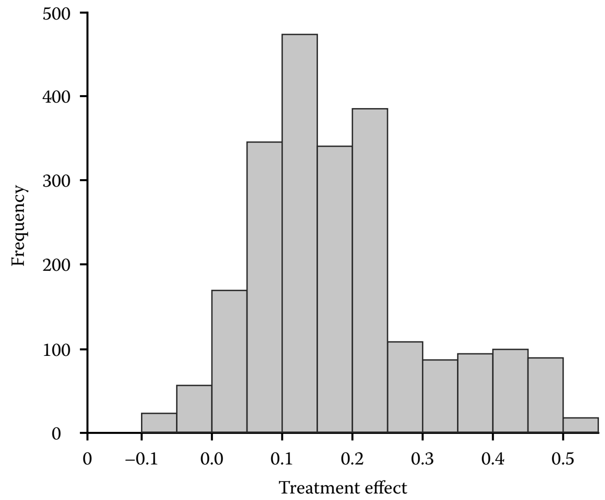

Figure 1. Distribution of treatment effects of Agricultural Socialisation Service on green grain production efficiency

Source: Author's elaboration

Table 6. Heterogeneity test of treatment effects of agricultural socialisation services on green grain production efficiency by farmer groups and land characteristics obtained by Generalised Random Forest model

Variable name	Ratio	Standard error
Average value	0.96***	0.12
Difference between groups	1.20***	0.18
Modelling	GRF	–
Observed value	2 279	–

*, **, ***significance at the 10%, 5%, and 1% levels, respectively, with standard errors given in parentheses; GRF – Generalised random forest

Source: Author's elaboration

Table 7. Heterogeneity in the treatment effects of Agricultural Socialisation Services on Green Grain Production efficiency by scale of household arable land operations and degree of land consolidation

Variable name	Group		Green grain production efficiency					Between-group difference test	
			observations (N)	ATE	standard error	T-value	confidence Interval (99%)	mean square	P-value (between-group)
Agricultural Socialisation Services	scale of household arable land operations	small-scale	1 033	0.366***	0.030	12.200	(0.308; 0.424)	37.07	<0.000 ***
		medium	700	–0.037	0.031	–1.194	(–0.099; 0.025)	–	–
		large-scale	546	0.127***	0.052	2.307	(0.025; 0.229)	–	–
	degree of land consolidation	0 = low	1 330	0.087***	0.030	2.900	(0.028; 0.146)	33.95	<0.000 ***
		1 = high	949	0.347***	0.029	11.966	(0.295; 0.411)	–	–

*, **, ***significance at the 10%, 5%, and 1% levels, respectively, with standard errors given in parentheses; ATE – average treatment effect

Source: Author's elaboration

derived greater benefits from ASS. However, ASS have a negative effect on medium-sized farmers.

DISCUSSION

Current research investigators have begun to explore agricultural technology services. Compared with previous studies, our research offers two key contributions.

Firstly, in terms of content innovation, although current studies seldom incorporate ecological factors such as carbon emissions into cost-benefit analyses, we used a three-stage super-efficiency SBM model in this study. This model includes carbon emissions as an undesired output and integrates fertilisers and pesticides as input variables. By excluding environmental factors' interference with green production efficiency, we obtained a credible and comparable dependent variable to investigate the effect of ASS on farmers' production.

Secondly, current research investigators have noted the heterogeneity among farmer groups; however, few have demonstrated the effect of such differentiation empirically. Moreover, existing methods may obscure the effect of agricultural technology services on individual heterogeneity. In this study, we leveraged the GRF algorithm to use its advantages fully, avoiding biases from the perceptual selection of covariates and achieving consistent estimation of treatment effect heterogeneity.

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The study's limitations include reliance on data from Jiangsu, a major economic and rice-producing province. Its unique geography and economy may limit the generalisability of findings to underdeveloped areas, non-rice regions or remote areas. Further research is essential to validate the applicability of these results in varied settings. In addition, although we examined the effect of differences in how farmers allocate their resources on the effectiveness of ASS at the margin, the variety of service providers and the range of services offered indicate that further research is needed. Investigators in future studies should assess the broader effect of these services, including their effects on the efficiency of green grain production and on farmers' incomes.

CONCLUSION

In this research, we used a combination of machine learning algorithms and traditional empirical methods in the social sciences to identify causality, empirically analysing the effect of ASS on the efficiency of green grain production. The main findings are as follows:

i) ASS significantly enhances green food production efficiency. First, although findings from prior studies have been divided on the effect of ASS on cost, efficiency and green production, our study results demonstrate that ASS substantially improve green food production efficiency. Second, our finding that ASS plays a pivotal role in pest and disease control and seedling production challenges results from current studies suggesting that pest and disease control increase costs. Contrary to the findings from these studies, our findings indicate that ASS does not inherently raise costs. Instead, ASS can reduce costs and amplify benefits by introducing new technologies and implementing large-scale pest and disease control measures. Farmers' practices, often based on personal experience, can lead to excessive pesticide use, increasing costs and environmental pollution, or insufficient use, which diminishes control effectiveness. Finally, an increase in ASS engagement correlates with a significant increase in green food production efficiency, suggesting that agricultural technical services are indeed efficacious.

ii) The scale of household farming significantly influences the role of ASS. ASS are particularly beneficial for small-scale farmers because of the constraints imposed by limited scale and extensive compartmentalisation, which render the acquisition of agricultural machinery economically impractical. These farmers, heavily reliant on manual labour and lacking a competitive edge in securing agricultural inputs, can benefit greatly from ASS. ASS have proven effective in facilitating the division of labour in production, replacing manual labour with mechanised operations, and reducing the cost of agricultural inputs through contractual agreements. Consequently, when scale is a limiting factor, ASS can markedly enhance production efficiency. Furthermore, research indicates (Ma et al. 2018) that ASS can facilitate smallholder farmers' integration into agricultural modernisation.

iii) In the study, we found that the degree of land contiguity has a significant effect on the role of ASS. For farmers with a high degree of land contiguity, ASS bring higher efficiency gains, which also is related to the characteristics of ASS, an important advantage of which is mechanisation. A high degree of land contiguity is conducive to low mechanisation costs. A low degree of land contiguity results in the need for agricultural machinery to operate in different plots, incurring additional costs and wasting time.

On the basis of these research findings, we have derived several insights. Firstly, there is a need to broaden the scope of agricultural technical services, fully harnessing their potential to enhance the efficiency of green grain production. Secondly, the effect of agricultural technical services on the efficiency of green grain production varies, highlighting the importance of tailored strategies to assist small-scale producers and those facing high levels of land fragmentation in addressing their challenges according to their specific circumstances.

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