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ECONOMIC IMPACTS OF DRYING SERVICE LAYOUT, TECHNOLOGY AND POLICY SUBSIDIES ON LARGE-SCALE RICE FARMING

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Abstract

This study investigated the effects of drying service accessibility and technological advancement on rice farmers' income using a spatial-technology-quality-income framework. Based on data from 465 farmers, the analysis showed that improved spatial accessibility and technological upgrades significantly increased net income. A one-minute reduction in travel time raised income by approximately 0.53 yuan per unit area, while a one-point increase in technology score led to a 145.7 yuan gain. Drying quality measured by mold rate served as a significant mediator. Each 1% reduction in mold rate corresponded to a 200 yuan increase in income. The benefits were more pronounced for large-scale farmers, highlighting the role of operational scale. Moreover, policy subsidies effectively boosted farmer income by 22% on average. These findings provide empirical support for targeted investment in drying infrastructure, technological improvements, and policy interventions to enhance the economic efficiency of post-harvest services and strengthen rural livelihoods.

Introduction

In the context of agricultural modernization and national food security strategies, enhancing the economic benefits of rice cultivation plays a vital role in ensuring rural income stability and sustainable development (Demurian 2025). As agricultural operations increasingly shift toward scale-based models, large-scale farmers and family farms have emerged as the dominant actors in rice production, with growing dependence on mechanized and post-harvest services (Müller *et al.* 2022). Among post-harvest processes, drying is particularly crucial as it directly influences rice quality (Chitsuthipakorn and Thanapornpoonpong 2022), mildew risk (Ying and Spang 2024), and product grade (Wang *et al.* 2023), all of which significantly affect market prices and farmer income. However, challenges such as poor spatial distribution of drying facilities, outdated technology, and low transport efficiency continue to constrain economic gains in rural areas (Babu *et al.* 2022).

While prior research has primarily focused on improving input-output efficiency during the production stage (Sapkota *et al.* 2021), the micro-level mechanisms through which post-production services like drying influence farmer income remain underexplored (Nosrati *et al.* 2022). Existing studies that do address drying services tend to examine their technical or economic optimization in isolation (Xu *et al.* 2022), or address broader accessibility issues within global supply chains (Malanon and Sumalde 2022). Yet, the pathways through which drying services, via quality improvements, translate into income gains have not been systematically quantified (Zhang *et al.* 2024). Recent insights suggest that drying quality may serve as a mediating factor (Mohammad and Dey 2025) and that service design must reflect the distinct needs of large-scale farmers (Cai *et al.* 2021).

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The aim of this study is to examine the economic effects of spatial accessibility and technological advancement in drying services on rice farmers' income, with a particular focus on large-scale farming contexts. Specifically, the study evaluates how the spatial layout of drying facilities influences service efficiency and income generation, how advanced drying technologies reduce post-harvest losses and enhance market value, and how rice drying quality mediates the relationship between service attributes and economic outcomes. In addition, the analysis considers the role of spatial optimization strategies and policy interventions in strengthening the performance of drying services and promoting income growth among large-scale farmers.

Materials and Methods

This study employed a mixed-methods approach combining field surveys, spatial data analysis, and expert evaluation to investigate the impact of drying service accessibility and technology on farmers' income. Data were collected from multiple sources, including field surveys, official statistics, and expert assessments, covering aspects such as spatial distribution of services, technical advancement, and economic outcomes. A stratified sampling strategy was applied to select 500 rice farmers from 10 townships, ensuring representation of 300 large-scale and 200 small- to medium-scale farmers. After data validation, 465 effective questionnaires were obtained. The survey captured information on production costs, drying methods, transport distances, rice quality, sale prices, and subsidy receipt. Drying service accessibility was measured using GPS tracking of farmer locations and drying facilities, and spatial accessibility indices were computed using GIS-based proximity and travel-time analysis. Technical performance of drying equipment was assessed using the Delphi method. Seven agricultural engineering experts rated equipment based on energy efficiency, temperature uniformity, and automation. Scores were aggregated to develop a composite technical advancement index. Auxiliary variables were derived from agricultural census data, disaster frequency records, government subsidy databases, and rice market price reports. These were used to construct a policy subsidy intensity index reflecting the proportion of subsidy relative to total agricultural expenditure. The final dataset integrated 465 farmer records, spatial and technical data for 52 drying service points, and multiple township-level variables. Follow-up surveys were conducted with 418 farmers to capture changes in income and technology adoption under policy interventions. A multiple linear regression (MLR) model was used to quantify the impact of drying accessibility and technology on net income per unit area. Mediation analysis was conducted using a three-stage regression framework, with rice mildew rate used as a proxy for drying quality. The Bootstrap method (5,000 replications) was employed to test the significance of indirect effects. To assess heterogeneity by farm size, separate MLR models were estimated for large and small-scale farmers, with Chow tests applied for structural difference analysis. A moderation model was further constructed by introducing interaction terms between farm size and core explanatory variables. Potential endogeneity of technology adoption was addressed using an instrumental variable (IV) approach, with regional historical density of drying facilities serving as the IV. A two-stage least squares (2SLS) method was used. Spatial patterns were visualized using ArcGIS. Hot spot analysis and a gravity model were applied to examine income clustering and service coverage intensity across regions.

Results and Discussion

Based on data collected from 465 farmer questionnaires, an integrated analysis of net income per unit area and drying service characteristics was conducted. Descriptive statistics, spatial visualization, multivariate regression, mediation modeling and heterogeneity analysis were employed to explore regional disparities and the influence of drying service quality and accessibility on economic outcomes.

To illustrate income distribution, a kernel density estimation method was applied using the Seaborn library and the resulting distribution curve is shown in Fig. 1. A right-skewed distribution was observed, indicating that most farmers were concentrated in the middle-to-high income ranges, while a smaller portion of the sample remained at the lower-income tail. These findings suggest that limitations in accessibility and technological diffusion still exist for a subset of the population.

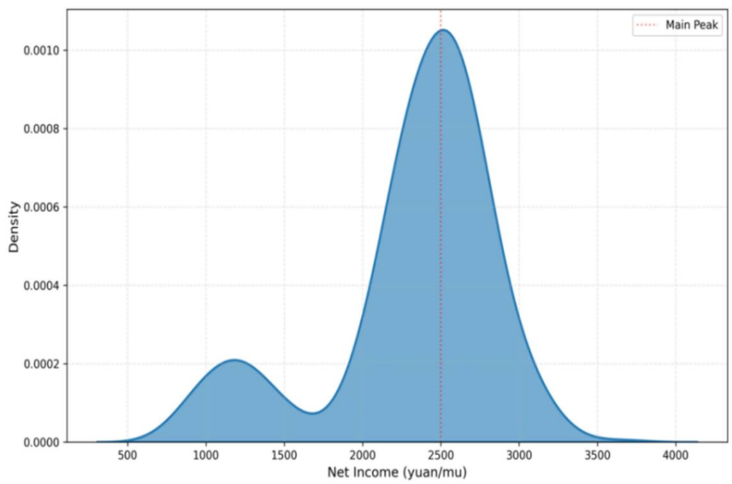

Fig. 1. Kernel density distribution of unit area net income.

The spatial layout of drying facilities was modeled using point density analysis in ArcGIS (Fig. 2). It was found that drying services were predominantly concentrated in the central grain-producing towns, while peripheral areas exhibited limited coverage. This "core agglomeration-edge sparsity" pattern reflected considerable geographic inequality in service access.

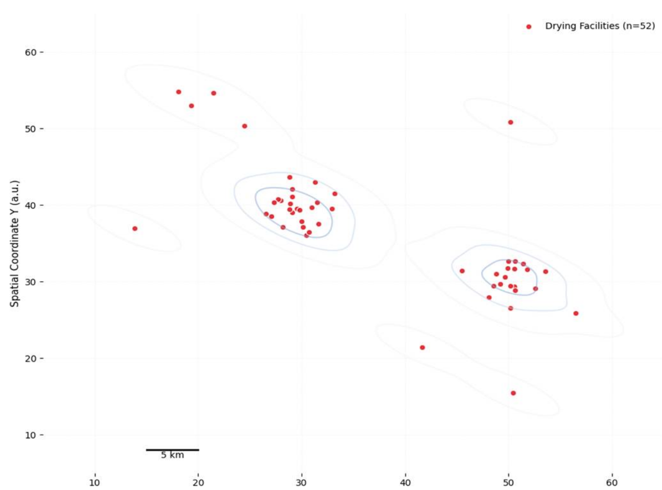

Fig. 2. Spatial distribution density map of drying service facilities.

In Fig. 3, box plots were used to display the technical scores assigned by farmers across various townships. Significant regional variation in service quality was revealed. In certain regions, wide fluctuations and low medians were identified, indicating instability in service delivery. These disparities underscored the need for subsequent modeling to account for regional heterogeneity and interaction effects.

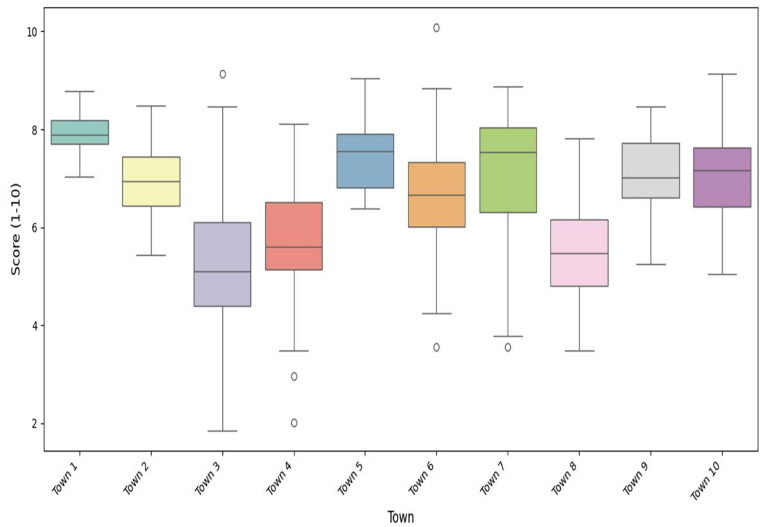

Fig. 3. Distribution map of drying service technology scores in different towns.

Descriptive statistics of key variables were summarized in Table 1. The mean net income per unit area was found to be 2,468.3 yuan/mu, with a range from 273.8 to 4,217.6 yuan. The average travel time to drying facilities was calculated at 28.7 minutes (SD = 12.3), while the mean technical score was 6.8 (range: 3-9). The mean mildew rate of rice was reported as 0.12%, with a range from 0.02 to 0.30%. Substantial heterogeneity across observations was therefore confirmed.

Table 1. Statistical results of key variables of the sample.

Variable name	Sample mean	Standard deviation	Maximum	Minimum
Net income per unit area (yuan/mu)	2468.3	480.5	4217.6	273.8
Drying service travel time (minutes)	28.7	12.3	55	10
Technical score (1-10 points)	6.8	1.4	9	3
Mildew rate of rice (%)	0.12	0.08	0.3	0.02

To further examine regional disparities, data were aggregated by township (Table 2). Average travel times ranged from 21 to 39 min, mildew rates from 0.05 to 0.20%, and technical scores from 6.2 to 7.4. Notable differences were identified between regions in terms of service responsiveness, post-harvest rice condition, and satisfaction levels.

A multivariate linear regression model was constructed to quantify the influence of service accessibility and quality on income (Table 3). Net income per unit area was used as the dependent variable, with travel time and technical score as core explanatory variables. Control variables included planting area, sales price, government subsidies, mechanization rate, and household labor input. Travel time was found to exert a significant negative effect (coefficient = -0.53, $p < 0.001$), indicating that each additional minute reduced income by 0.53 yuan/mu. Conversely, technical score exhibited a significant positive effect (coefficient = 145.7, $p < 0.001$), with each additional point increasing income by 145.7 yuan/mu. The effects of planting area, sales price, mechanization rate, and labor input were all found to be positive and statistically significant, resulting in average income increases of 48.3, 195.2, 98.4 and 46.7 yuan, respectively. Government subsidies were also associated with a significant income gain of 295.6 yuan ($p = 0.012$). An R^2 of 0.74 was achieved, indicating a high degree of model fit.

Table 2. Mean statistical table of travel time, mildew rate, and technical score of each township.

Township	Average travel time (minutes)	Average mildew rate (%)	Average technical score (1-10)
1	24	0.14	7.1
2	29	0.15	7.0
3	34	0.08	6.3
4	27	0.13	6.4
5	21	0.05	7.4
6	39	0.18	6.6
7	19	0.09	7.3
8	31	0.11	6.2
9	26	0.07	7.0
10	37	0.20	6.7

Table 3. Multiple linear regression estimation results of drying service accessibility and technical score on net income.

Variable name	Regression coefficient	Standard error	p-value
Drying service travel time (minutes)	-0.53	0.12	0.001
Technical score (1-10 points)	145.7	19.8	0.000
Planting area (mu)	48.3	9.7	0.005
Sales price (yuan/kg)	195.2	28.3	0.002
Government subsidies	295.6	47.3	0.012
Mechanization rate (%)	98.4	14.6	0.004
Household labor input (person)	46.7	9.2	0.006
Constant term	980.5	195.3	0.000

Model fit: $R^2 = 0.74$.

A mediation effect model was constructed to examine whether travel time and technical score influenced income indirectly through the mildew rate of rice. The path structure "travel time/technical score → mildew rate → income" was specified, and the Bootstrap method was employed for inference (Table 4). The total effect of travel time on income was estimated at -0.087, with a direct effect of -0.061 and an indirect effect of -0.026. These results confirmed that income was reduced both directly and through the increased mildew rate caused by longer travel times. Similarly, the total effect of technical score was calculated at 0.135 with a direct effect of 0.105 and an indirect effect of 0.030, suggesting that improvements in technical service quality not only increased income directly but also did so indirectly by reducing mildew incidence.

Table 4. Mediation model effect decomposition results and confidence interval record.

Independent variable	Effect type	Estimated value	95% Bootstrap confidence interval	Significant (P <0.05)
Travel time	Total Effect	-0.087	[-0.143, -0.029]	Yes
	Direct Effect	-0.061	[-0.115, -0.006]	Yes
	Indirect Effects	-0.026	[-0.049, -0.008]	Yes
Technical score	Total Effect	0.135	[0.072, 0.199]	Yes
	Direct Effect	0.105	[0.045, 0.166]	Yes
	Indirect Effects	0.030	[0.010, 0.058]	Yes

The heterogeneous effects of technical service quality on income were examined by including interaction terms between technical score and farm size. Marginal effects were calculated and are presented in Fig. 4. It was observed that the marginal benefit of improved technical score was significantly greater for farmers with larger-scale operations. This indicates that economies of scale enhanced the income effect of technological improvements, while small-scale farmers benefited less, potentially due to limited adoption capacity.

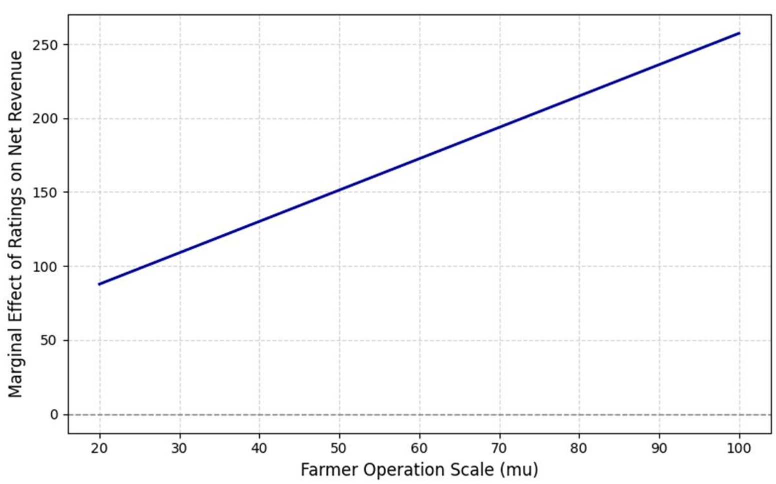

Fig. 4. Technology score on marginal effect of unit net income.

To evaluate the effect of subsidy policies, follow-up data from 418 households were analyzed (Fig. 5). Farmers who received subsidies were found to achieve a net income of 2,715.4 yuan/mu, approximately 22% higher than the 2,223.6 yuan/mu of non-subsidized farmers. Yield increases

(128.2 kg vs. 45.7 kg), market price premiums (62.3 yuan/ton vs. 35.8 yuan/ton) and cost savings (143.9 yuan/mu vs. 58.6 yuan/mu) were also all significantly higher among the subsidized group. These results confirmed the effectiveness of subsidy policies in enhancing productivity, market value and profitability.

This study reveals how drying service accessibility, technological quality and policy interventions shape rice incomes of farmer, while exposing spatial and scale-based disparities. The right-skewed income distribution and "core-periphery" facility clustering highlight infrastructure inequalities, with longer travel times reducing income (-0.53 yuan/mu per minute), aligning with Minten *et al.* (2016). Decentralizing drying hubs and improving rural transport could mitigate these gaps.

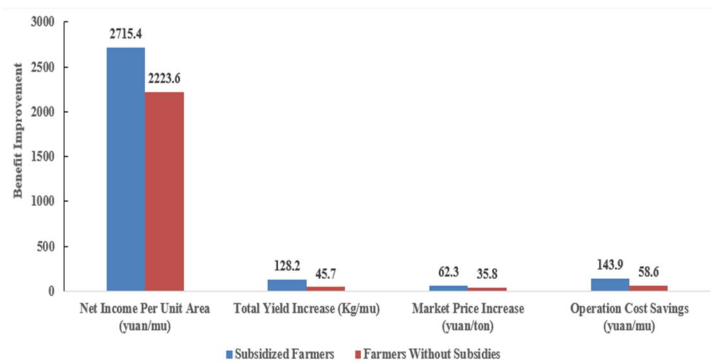

Fig. 5. Comparative analysis of farmers with technology subsidies and non-subsidized farmers in the dimension of income structure.

Advanced drying technologies boosted income (145.7 yuan/mu per technical score unit), supporting Wang *et al.* (2023) on quality-value linkages. Mediation analysis confirmed mildew rate transmits 30% of this effect, validating Mohammad and Dey (2025). However, large-scale farmers benefited disproportionately due to adoption economies (Foster and Rosenzweig 2010), necessitating targeted smallholder training and subsidies (Cai *et al.* 2021).

Subsidies raised incomes by 22% via yield, price and cost gains (Bellemare *et al.* 2013), but risked favoring larger farms. Means-tested schemes (Zhang *et al.* 2024) could enhance equity. The "space-technology-quality-income" model advances post-harvest service analysis (Nosrati *et al.* 2022), with practical implications: GIS-driven facility expansion, tiered technology promotion and dynamic subsidies.

Limitations include cross-sectional data and unobserved adoption barriers. Future research should explore longitudinal climate impacts and digital solutions (Xu *et al.* 2022). Addressing spatial, technological, and policy gaps can optimize post-harvest efficiency and equitable income growth.

Based on field data, this study revealed how the convenience and technical quality of drying services significantly enhanced farmers' net income by improving drying effectiveness. Income growth was influenced by factors such as planting scale, sales price and policy subsidies. Spatial analysis indicated regional income clustering, reflecting imbalances in service distribution. However, the study faced limitations, including reliance on subjective evaluations, a limited sample area, and the use of cross-sectional data. Future research should employ panel data and experimental methods, expand to other crop types and explore smart drying technologies and policy incentives to support sustainable agricultural development.

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