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Impact of land fragmentation on rice producers' technical efficiency in South-East China

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ABSTRACT

Rice farming is important for income generation in large parts of China and Asia. This paper uses detailed household, crop- and plot-level data to investigate the levels and determinants of rice producers' technical efficiency for three villages with different characteristics in a major rice-growing area of South-East China, focusing in particular on the impact of land fragmentation. Empirical results obtained by applying a stochastic frontier model showed statistically significant differences in technology level among villages, with the remotest village having the lowest technology level. Within villages average technical efficiency was generally high, ranging from 0.80 to 0.91 for the three types of rice that are grown in the region. For late-rice producers, no statistically significant variation was found in their technical efficiencies. Land fragmentation was found to be an important determinant of technical efficiency in early-rice and one-season rice production. An increase in average plot size increased rice farmers' technical efficiency. Given average plot size, an increase in the number of plots was found to increase technical efficiency, indicating the presence of variation effects. A larger distance between homesteads and plots contributed to technical inefficiency in early-rice production. The high levels of technical efficiency found in our study support the view that to raise rice productivity in the long run, new technologies need to be introduced.

1. Introduction

Rice is the staple food for 3 billion people worldwide. Of the world's 1.1 billion poor people with an income of less than one dollar per day, almost 700 million reside in the rice-growing countries of Asia, including China. Throughout China, rice is grown on 20% of its cultivated area and constitutes 48.2% of its grain production; besides, over 58% of the Chinese population use rice as main staple food [1]. Rice farming is therefore important for food self-sufficiency and income generation in large parts of China. However, land fragmentation may be a major bottleneck for improving productivity in rice farming [2,3], as found in other Asian countries [4,5]. Due to high population pressure, the limited availability of arable land and the prevailing system of land use rights distribution, land fragmentation in China is very severe. In 1999, farm households in China cultivated on average an area of 0.53 ha, spread over 6.06 plots [6].

In this paper we intend to examine the levels and determinants of rice producers' technical efficiency (TE), focusing in particular on the impact of land fragmentation, with the aim to investigate to what extent rice production can be improved under existing technologies.

Experiences with quantifying the impact of land fragmentation on agricultural production efficiency at micro level in China are scarce. Available studies include Nguyen et al. [7], who used data from a survey conducted among 1200 households in Jilin, Shandong, Jiangxi, Sichuan and Guangdong Provinces in 1993–1994 to examine the impact of land fragmentation on the productivity of three major grain crops. The results indicate that controlling for total holding size, there is a statistically significant and positive relationship between plot size and output of maize, wheat and rice. Wan and Cheng [3] explored the impact of land fragmentation and returns to scale in the Chinese farming sector, using the same rural household survey data set. Their main finding was that an increase in land fragmentation by one plot leads to output losses of 9.8%, 6.5% and less than 2%, in root and tuber crops, wheat and other crops, respectively. Earlier research undertaken by Fleisher and Liu [2] used data from a survey among 1200 households in Jilin, Jiangsu, Henan, Hebei and Jiangxi Provinces in 1987–1988 to examine the effect of land fragmentation, as measured by number of plots, on productivity. Their main finding was that the number of plots had a negative impact on agricultural production. They estimated that a 10% increase in the number of plots resulted in a 5.7%

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reduction in output. These studies used partial measures to examine efficiency and failed to distinguish between the productivity differential caused by land fragmentation and by other factors like farmer's age (experience) and education level. Methods that can deal with these deficiencies are required for obtaining improved estimates of the impact of land fragmentation on TE. In a recent study of the impact of land rental market participation and off-farm employment on TE for 52 households in three villages in north-east Jiangxi, Feng [8] included the number of plots and the distance to the homestead among the control variables. His study showed that the number of plots had a negative impact on TE whereas the distance to the homestead was not statistically significant.

Commonly used approaches in efficiency analysis distinguish parametric and non-parametric methods. Empirical analyses of agricultural producers' efficiency, using both Stochastic Frontier Analysis (parametric method) and Data Envelopment Analysis (non-parametric method) approaches, are in abundance [9–13]. During the last decades, many studies have applied efficiency measurement to the agricultural sector, using frontier methods [14–20]. Relatively recent work includes Chen and Song [21], who used meta-frontier analysis to investigate the efficiency and technology gap in China's agriculture. Studies that investigated efficiency in rice production include Daryanto et al. [22], who analysed the technical efficiencies of rice farmers in West Java, and Coelli et al. [23], who applied non-parametric methods to analyse rice cultivators' efficiency in Bangladesh. Although the latter study used one of the most exhaustive lists of farm-specific variables that any efficiency analysis has used, land fragmentation was not included.

Among the numerous empirical applications, only few have taken land fragmentation into account. A study by Hazarika and Alwang [24] showed that plot size had a significant positive effect on cost efficiency of tobacco cultivators in Malawi. Research from Bangladesh [25] indicated that on average farmers with larger plots operated at higher levels of technical and allocative efficiency. On the other hand, land fragmentation measured by number of plots and distance was found to have no statistically significant effect on the efficiency of Nepal's rice producers [12]. Sherlund et al. [26] tested smallholder technical efficiency, controlling for plot-specific environmental conditions, in Ivory Coast, using 464 traditional rice plots. TE was found to be higher for those who cultivated three or more rice plots.

Recent research by Rahman and Rahman [27], who examined the impact of land fragmentation and resource ownership on rice producers' TE in southern Bangladesh, using data from 298 farms surveyed in early 2000, found that a 1% increase in land fragmentation decreased efficiency by 0.03%. They used the number of plots farmed to measure land fragmentation. Chen et al. [28] examined TE of farms in China's four major regions, using farm household panels covering the late 1990s. They found that land fragmentation, as measured by the Simpson index, was detrimental to efficiency, controlling for the number of plots. TE increased when the number of plots increased from the first quartile to the second and from the second to the third, but decreased when the number of plots increased from the third to the highest quartile. In their paper, different fertilizers were aggregated in terms of their monetary value per household. The field survey conducted for our research indicates, however, that farmers tend to use at least five kinds of fertilizer[1] with different contents of nitrogen, phosphorus and potassium. Because crops may have different responses to different types of fertilizer, a method that simply aggregates the different types of fertilizer into one variable cannot reflect the real crop response to each fertilizer type. Farmers may overuse some kind of fertilizer while underusing another. As Huang [29] pointed out, fertilizer application in China is unbalanced. In this study we shall therefore distinguish fertilizers into nitrogen, phosphorus and potassium in terms of their active contents, i.e., N, P_2O_5 and K_2O, respectively.

In this paper we use detailed household, crop- and plot-level data while controlling other factors, to examine the impact of land fragmentation on rice producers' TE, using a stochastic frontier model. A major difference between our study and previous studies is the way in which land fragmentation, fertilizer and soil quality are measured. For land fragmentation we used a set of indicators that measure its different dimensions, fertilizer use was measured (as mentioned above) by the active macro-nutrient contents, while soil quality was measured by asking farmers' subjective opinions. The remainder of the paper is structured as follows. Section 2 describes the data and sampling frame, while Section 3 discusses the model specification. Results are presented and discussed in Section 4. Section 5 summarizes and elaborates the major conclusions.

2. Sampling and data collection

Data used for this study were collected during a household survey conducted in 2000 and 2001 in three villages in north-east Jiangxi province, covering the agricultural season of the year 2000. The villages Banqiao, Shangzhu and Gangyan were chosen to reflect differences in the degree of market access and agricultural and economic development. They show a high degree of variation in natural resource endowments, rural infrastructure, and land fragmentation, and are considered to be representative of a much larger rice producing, hilly area in Jiangxi and probably also in neighbouring provinces (see Kuiper et al. [30] for details).

Banqiao is the smallest village with around 900 persons distributed over 220 households. Located in a hilly area, 60–70% of its total surface is upland. Market access is good: Banqiao is within 10 km distance from a major city, Yingtan, but the roads from its hamlets to the main road are in poor condition. Irrigation conditions are adequate; paddy fields can be easily irrigated with water from a reservoir, against payment of irrigation fees. In its dryland area, rain-fed agriculture is practised for growing groundnut, fruits, and other cash crops.

Shangzhu is a remote village; it takes about 2 h by bus from the county seat of Guixi county to the major hamlet. Its 16 hamlets are scattered over a mountainous area, with some of them very difficult to reach. The upland area accounts for 97% of its farmland area. In Shangzhu there are 472 households with 2028 persons. The main crops are rice and bamboo. Rice is planted on the terraces of the valley areas, whereas bamboo and fir (a kind of cash tree) are grown in the hilly areas. The terraces are well-constructed with stone, and are several hundreds of years old.

Gangyan is the largest village, with 730 households and 3200 persons. It is located in a plain area at about 30 km distance from the county seat of Yanshan county. Roads are in good condition. The main crops in this village are rice and vegetables. Tractors are used and most of the plots can be irrigated against payment of irrigation fees.

Farmland (irrigated and non-irrigated land) per capita equals 1.89 mu[2] in Banqiao, 1.36 mu in Shangzhu and 1.21 mu in Gangyan. Households were selected randomly. Around 23% of the households were interviewed in each of the selected villages, resulting in 339 surveyed households. Detailed information from 2490 plots was collected. Among the 339 households selected, 264 planted

[1] Farmers used urea, ammonium bicarbonate, compound fertilizer with different nitrogen, phosphorus and potassium combinations, calcium magnesium phosphate and potassium chloride.

[2] 1 mu = 1/15 ha.

early rice, 206 one-season rice, and 261 late rice. The average number of plots per household was about the same in the three villages, equaling 7.36, 7.44 and 7.36 for Banqiao, Shangzhu and Gangyan, respectively. The average distance from the homestead to the plots was a 14-, 17- and 16-min walk for Banqiao, Shangzhu and Gangyan, respectively.

The household data obtained from this survey were also used by Feng [8]. In his study the data for a sub-set of 52 households were combined with plot-level data for 215 plots to estimate the impact of land rental market development and off-farm employment on TE at the plot-level. Our study used the full household sample to examine the impact of different dimensions of land fragmentation on TE at the household level.

3. Model specification

We chose the stochastic frontier approach to analyse the impact of land fragmentation on rice producers' TE. The main reason for this choice is that rice production in China is subject to weather disturbances and heterogeneous environmental factors like soil quality and irrigation access; moreover, the respondents might not have precisely answered some of the questions due to e.g., varied perceptions, and therefore have affected measured efficiency.

The parameters of the stochastic frontier and the inefficiency model were estimated simultaneously, following Battese and Coelli [20]. The Frontier 4.1 software package developed by Coelli [31] was used for this purpose.

Typical agricultural inputs like land area, labour and material inputs used in rice production were included in the production frontier. Unlike other studies, we separated fertilizer into the three macro-nutrients required for crop growth, as explained above.

The production frontier to be estimated is specified as:

$$\ln(Q_i) = \beta_0 + \sum_{j=1}^{7}\beta_j \ln X_{ij} + \frac{1}{2}\sum_{j=1}^{7}\sum_{k=1}^{7}\beta_{jk} \ln X_{ij} \ln X_{ik} + \sum_{l=1}^{2} D_{il} + v_i - u_i \quad (1)$$

where $\ln(Q_j)$ is the logarithm of rice output (either early rice, one-season rice or late rice) on farm i, X_j are inputs used in each season's rice production, D_l are village dummies, v_i are stochastic random errors, and u_i are non-negative random errors accounting for TE in production. A translog specification was chosen because it represents a second-order approximation to any true functional form and it places fewer restrictions before estimation than a Cobb–Douglas specification or other more traditional specifications.

The variables X_1–X_7 represent rice planting area, labour use, nitrogen, phosphorus, potassium, seed, and chemical inputs (herbicides and pesticides), respectively. Phosphorus was expected to affect rice production during several years after its application. We did not have data on phosphorus applications in previous years. But given that household fertilizer application patterns tend to be relatively stable over time, it was assumed that phosphorous application in the current season was highly correlated with application levels in preceding seasons. Hence, the estimated coefficient in a cross-section analysis will reflect its long-term impact. Tractor use was converted into oxen according to its cost (rent), because tractors can be easily substituted for oxen. In this study, one day of tractor use equals 7 days of oxen use. Village-specific variables, like market access, extension services, and climate differences, are represented by the village dummies D_1 and D_2 for Shangzhu and Gangyan, respectively.

Table 1
Definition of explanatory variables, and their expected signs, in the TE equation.

Variable	Name	Unit	Expected sign
Age of household head	Age	year	+
Education of household head	Edu	year	+
Household size	Hhsize	person	+/−
Share of labour force members in household	Shlab	%	+
Number of plots	Nplot	plot	−/+
Average plot size	Psize	mu	+
Average distance from plots to homestead	Dist	min	−
Share of land with good soil quality	Soil1	%	+
Share of land with medium soil quality	Soil2	%	+
Dummy, =1 if household saved money	Dsave	–	+
Dummy, =1 if household received credit	Dcred	–	+
Dummy, =1 if household owned oxen or tractor	Doxen	–	+

The efficiency model is specified as

$$TE_i = \delta_o + \sum_{j=1}^{12}\delta_j Z_j \quad (2)$$

where TE_i represents the efficiency score of each household obtained from Eq. (1). The Z variables represent factors that may influence farmer's efficiency.

The most frequently used variables in the empirical analysis of TE are farmer's education and experience, contact with extension, access to credit, farm size, land tenure, and environmental and non-physical factors, like information and supervision, which may influence the capability of producers to utilize the available technologies. What indicators should be used in the model depended on the relevant conditions in the research area and the availability of data.

In our case, the following factors were used for explaining TE: age and education of the household head; household size and share of labour force members in the household; land fragmentation; soil quality; savings, access to credit; and oxen ownership. The definitions of the explanatory variables used in the TE equation, and their expected signs, are presented in Table 1.

In areas with traditional farming systems, age is a proxy for farming experience. The impact of age on TE in such traditional systems is positive. A higher level of education can lead to a better assessment of the importance and complexities of production decisions, resulting in a better arrangement of farming practices. The anticipated sign of the impact of education on efficiency is therefore positive. A larger household size may mean that more labour is available for field work but also that more time is needed for housework (taking care of the children, for example), and thus the impact of household size on efficiency is mixed. A larger share of labour force members in a household usually implies more labourers and thus more time to be devoted to activities such as timely irrigation, pest management and harvesting, all leading to a higher TE.

The number of plots, average plot size and average distance of the plots to the homestead were used to capture the impact of land fragmentation on TE. A large number of plots may enable households to benefit from variation in local agro-climatic conditions, such as sunshine, precipitation, slope or soil depth, by distributing their own labour over the seasons and tuning the choice of rice varieties to these conditions ('variation effect'). On the other hand, a large number of plots may cause inefficiencies in water management and overall farm management ('management effect'). If the variation effect exceeds the management effect, its overall impact on TE will be positive. Compared with small plots, larger plots encourage the use of modern technologies and thus the average plot size is expected to have a positive impact on TE. A larger average distance to the plots means more loss of time and inconvenience in farming management, having a negative impact on TE.

In the surveyed areas, farmers were asked to classify their plots' soil fertility according to their perceptions of soil colour, topsoil depth, soil texture and workability into good, medium or bad, scored as 1, 2 and 3, respectively. The soil quality indicators were derived by calculating the share of plots planted with early (or late, one-season) rice with good and medium soils, respectively. The soil quality indicators are expected to be positively related to TE, because fertilizer response and other conditions for crop growth are higher on soils of a better quality.

Savings and availability of credit reduce monetary constraints on production, facilitating to obtain the inputs needed for production on a timely basis. Hence, both are supposed to increase efficiency. If a farm household owns oxen, land preparation can be carried out more timely and carefully and hence more efficiently.

4. Emperical results and discussion

Table 2 presents the descriptive statistics for the variables used in the analyses. The average area used for rice cultivation was about 5 mu per household, with large variations among households. The corresponding rice production varied from about 100 kg to more than 10,000 kg. Average yields equaled 4.3, 4.7 and 4.8 Mg ha^{-1} for early, one-season and late rice, respectively. Land fragmentation showed substantial variation between the three rice types. On average, the respondent's households used 3.1 plots to cultivate early rice, and 3.2 and 3.7 plots for one-season and late-rice production, respectively. Households tended to use the best plots for early-rice production, i.e., the plots with the best soil quality, the shortest distance to the homestead and largest size. On the other hand, they tended to use the plots with smallest average size, largest distance and lowest soil quality for one-season rice production.

Truncated normal distributions were assumed for the frontier functions of each rice type. The estimation results showed that the null hypothesis of γ being equal to zero could not be rejected for the late-rice model. The u term should therefore be removed from this model, leaving a specification with parameters that can be consistently estimated using ordinary least squares. We first discuss the results of the frontier functions for each rice type, and then turn to the results of the efficiency model.

4.1. Results of production frontier functions

The results of each production frontier model are presented in the upper part of Table 3. The corresponding input–output elasticities and marginal effects of each input are shown in Table 4. The sum of the estimated input coefficients is 0.93, 0.89 and 0.78 for early rice, one-season rice and late rice, respectively. This is consistent with Chen et al. [32], who estimated elasticities of scale equal to 1.00 for the north, 0.92 for the north-east, 0.88 for the east and 0.78 for the south-west of China, respectively. Similar to Chen et al. [32] and Fleisher and Liu [2], land in our study had the largest elasticity. However, in our study its value equaled 0.85 for early and one-season rice and 0.78 for late rice, whereas it ranged from 0.35 to 0.60 in the two aforementioned studies, indicating that land is a very crucial input in rice production in our survey area. A 1-mu increase in sowing area of early rice, one-season rice and late rice was estimated to increase production by 241, 263 and 252 kg, respectively. The estimated elasticities and marginal effects for the three macro-nutrients differed considerably from each other in each of the three production frontiers. Potassium had the largest marginal effect in early and in late-rice production, whereas the marginal effect of nitrogen was largest in one-season rice production. This confirms that crop responses differ with different types of fertilizer.

The estimated coefficients of the village dummies for Shangzhu and Gangyan were negative and significantly different from zero. Their values were largest in absolute size for Shangzhu, the most remote village. Farmers in this village were therefore operating at a lower technology level than farmers in the two other villages. The level of technology was highest in Banqiao, the village that was

Table 2
Descriptive statistics of variables used.

	Early rice				One-season rice				Late rice			
	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD
Values of production function variables												
Production	4000	125	1432	884	13200	75	1462	1276	7000	100	1817	1200
Land	16.0	0.4	5.03	3.03	33	0.40	4.70	3.63	23.0	0.30	5.62	3.47
Labour[a]	179	5.0	60.9	32.4	269	1.00	65.5	47.7	307	2	59.6	39.6
Nfert	524	2	104	81	328	0	72.5	62	743	0	114	97
Pfert	750	0	148	149	1172	0	82.5	126	1043	0	136	168
Kfert	250	0	38	47	394	0	22.1	35.	392	0	50.5	66.5
Seed	17	0	3.53	2.58	31.4	0.04	3.21	3.39	23.6	0.18	3.73	3.39
Chem	437	0.99	60.9	50	524	0	56.2	56.4	467	0.00	79.4	72.6
Values of technical efficiency model variables												
Age	75	23	47.0	10.3	75	27	47.2	9.94	75	23	47.0	10.1
Edu	12	0	4.70	2.75	13	0	4.71	2.84	12	0	4.69	2.70
Hhsize	14	1	4.55	1.55	14	1	4.54	1.57	14	1	4.56	1.56
Shlab	100	0	75.0	20	100	0	74.0	21	100	0	75.0	20
Nplot	15	1	3.13	2.10	9	1	3.21	2.12	15	1	3.69	2.34
Dist	35	1	12.6	6.76	75	0	20.5	12.4	45	1	12.8	7.35
Psize	9	0.25	1.90	1.11	8	0.34	1.55	0.94	9	0.30	1.79	1.10
Soil1	1	0	0.41	0.38	1	0	0.13	0.28	1	0	0.29	0.46
Soil2	1	0	0.44	0.38	1	0	0.40	0.41	1	0	0.48	0.50
Dsave	1	0	0.52	0.5	1	0	0.52	0.5	1	0	0.53	0.50
Dcred	1	0	0.45	0.5	1	0	0.42	0.49	1	0	0.43	0.50
Doxen	1	0	0.69	0.47	1	0	0.68	0.47	1	0	0.73	0.44

[a] Including travelling time to the plot.

Table 3
Results of frontier function model with rice producers' technical efficiency determinants.

Production frontiers	Early rice			One-season rice			Late rice		
	Coeff	*T*-ratio	Sig.[a]	Coeff	*T*-ratio	Sig.[a]	Coeff	*T*-ratio	Sig.[a]
Constant	6.155	10.44	***	5.850	12.56	***	5.902	9.540	***
ln(land)	1.149	3.488	***	0.400	1.374		0.319	0.896	
ln(labour)	−0.260	−0.915		0.222	1.106		−0.007	−0.031	
ln(Nfert)	−0.067	−0.317		0.289	1.648	*	0.481	2.339	***
ln(Pfert)	−0.097	−0.907		0.263	1.607		−0.018	−0.216	
ln(Kfert)	−0.029	−0.212		−0.337	−1.516		0.047	0.318	
ln(seed)	−0.106	−0.646		0.500	3.281	***	0.229	1.427	
ln(chem)	0.213	1.537		−0.188	−1.128		−0.210	−1.182	
Shangzhu	−0.133	−3.126	***	−0.477	−4.905	***	−0.406	−6.371	***
Gangyan	−0.115	−3.035	***	−0.227	−2.754	***	−0.100	−2.128	**
$\ln(\text{land})^2$	−0.164	−1.231		−0.223	−1.256	*	−0.084	−0.452	
$\ln(\text{labour})^2$	−0.013	−0.157		−0.037	−0.506		0.006	0.130	
$\ln(\text{Nfert})^2$	0.064	1.287		−0.078	−1.804	*	−0.055	−1.145	
$\ln(\text{Pfert})^2$	0.022	2.004	**	−0.011	−0.667		−0.015	−1.251	
$\ln(\text{Kfert})^2$	0.039	2.215	**	−0.018	−0.664		−0.006	−0.233	
$\ln(\text{seed})^2$	0.055	1.321		−0.034	−1.077		0.011	0.332	
$\ln(\text{chem})^2$	−0.040	−1.407		0.011	0.244		0.016	0.442	
ln(land) × ln(labour)	-0.069	−0.776		0.044	0.517		0.140	1.881	*
ln(land) × ln(Nfert)	0.028	0.415		0.060	1.133		0.103	1.322	
ln(land) × ln(Pfert)	−0.042	−1.342		−0.002	−0.055		−0.025	−0.639	
ln(land) × ln(Kfert)	−0.019	−0.486		0.009	0.161		0.016	0.339	
ln(land) × ln(seed)	0.095	1.748	*	0.174	3.940	***	0.030	0.445	
ln(land) × ln(chem)	0.061	1.350		0.058	1.140		−0.043	−0.664	
ln(labour) × ln(Nfert)	0.055	0.959		−0.012	−0.362		−0.062	−1.173	
ln(labour) × ln(Pfert)	0.017	0.552		−0.053	−1.220		0.036	1.463	
ln(labour) × ln(Kfert)	−0.025	−0.758		0.010	0.191		−0.082	−1.902	*
ln(labour) × ln(seed)	0.039	0.884		−0.085	−2.148	**	−0.004	−0.117	
ln(labour) × ln(chem)	0.042	1.011		0.042	0.903		0.035	0.787	
ln(Nfert) × ln(Pfert)	−0.004	−0.254		0.004	0.273		−0.006	−0.317	
ln(Nfert) × ln(Kfert)	0.012	0.587		0.045	1.316		0.001	0.021	
ln(Nfert) × ln(seed)	−0.048	−1.490		−0.046	−1.722	*	−0.013	−0.321	
ln(Nfert) × ln(chem)	−0.108	−2.508	**	−0.014	−0.411		−0.025	−0.820	
ln(Pfert) × ln(Kfert)	−0.022	−2.653	***	0.022	1.832	*	0.006	0.508	
ln(Pfert) × ln(seed)	0.021	0.772		0.009	0.634		−0.016	−0.883	
ln(Pfert) × ln(chem)	0.022	1.021		−0.020	−0.790		−0.005	−0.332	
ln(Kfert) × ln(seed)	−0.012	−0.405		−0.031	−1.907	*	0.016	0.689	
ln(Kfert) × ln(chem)	0.032	1.231		0.017	0.350		0.058	2.037	**
ln(seed) × ln(chem)	−0.031	−0.973		−0.038	−1.592		−0.042	−1.424	
Technical efficiency									
Constant	−0.991	−2.125	**	−1.235	−1.963	**			
Age	0.013	1.770	**	0.003	0.458				
Edu	0.073	1.909	**	0.038	1.443	*			
HHsize	−0.048	−1.780	*	0.062	1.171				
Shlab	−0.241	−1.161		0.363	0.879				
Nplot	0.132	2.115	**	0.104	1.703	**			
Psize	0.272	1.616	*	0.201	1.595	*			
Dist	−0.022	−1.801	**	−0.008	−1.213				
Soil1	0.249	1.492	*	−0.119	−0.579				
Soil2	0.112	0.938		0.195	1.275				
Dsave	0.133	0.992		0.469	1.329	*			
Dcred	0.115	1.503	*	0.232	1.383	*			
Doxen	−0.007	−0.108		0.573	1.300	*			
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.067	1.963	**	0.228	1.802	*	0.061	3.160	***
$\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$	0.719	4.212	***	0.984	80.38	***	0.388	1.095	
σ_v^2	0.048		0.004						
σ_u^2	0.019		0.224						
Log likelihood[b]	107		54.02		32.28				
LR test of the one-side error[b]	37.61.		61.68		0.145				
No. of observations	264		206		261				

[a] Statistical significance levels. $^*p \leq 0.1$; $^{**}p \leq 0.05$; $^{***}p \leq 0.01$ (note: variables with either a plus- or a minus-sign in Table 1 were tested one-sided).
[b] The critical value for the LR test is 26.2 ($p \leq 0.01$).

located closest to a major city and that was involved most in cash crop production.

4.2. Results of technical efficiency models

The bottom rows of Table 3 present the results for the error terms specified in Eq. (1). The value of the generalized likelihood ratio in the late-rice model was lower than the critical value, suggesting that there was no statistically significant variation in TE among the late-rice producers. On the other hand, the values in early rice and one-season rice were higher than the critical value, implying that the TE scores among early-rice producers and one-season rice producers were significantly different. The estimates of the variance parameters σ^2 and γ were significantly different from zero in early-rice and one-season rice production, indicating that (in)efficiency significantly affected the level and variation of out-

Table 4
Input-output elasticities and marginal effects.

	Early rice		One-season rice		Late rice	
	Elasticity	Marginal effect	Elasticity	Marginal effect	Elasticity	Marginal effect
Land	0.848	241	0.845	263	0.781	252
Labour	0.023	0.54	0.020	0.45	−0.046	−1.39
Nfert	0.034	0.47	0.056	1.12	0.011	0.17
Pfert	0.027	0.26	0.011	0.20	−0.038	−0.50
Kfert	0.024	0.89	−0.031	−2.06	0.025	0.91
Seed	−0.035	−14.3	0.009	3.92	0.108	52.62
Chem	0.007	0.16	−0.020	−0.52	−0.060	−1.38
Scale elasticity	0.927		0.890		0.782	

Calculated by authors from the coefficients of input factors in Table 3 and the mean values of the logarithms of production and input factors.

put of farm households. In the one-season rice model, the estimated parameter γ was close to 1 (0.98), suggesting that the variation in production was mainly caused by variation in efficiency; σ^2 was strongly biased towards σ_u^2 (0.224 over 0.004) and the generalized likelihood ratio statistic value confirmed this.

Regression results for Eq. (2) are presented in the second part of Table 3. Age and education were found to have statistically significant positive effects on TE in early-rice production, whereas education had a significant positive effect on TE in one-season rice production. This suggests that older farmers or farmers with more education were more experienced than their younger or less-educated counterparts, especially in early-rice production. A possible explanation is that early-rice cultivation is more complicated than one-season rice production, especially regarding nurseries.

Household size had a statistically significant negative impact on TE in the early-rice model, and had no significant effect on one-season rice. This result does not confirm the finding by Audibert [11] in Mali that larger families tended to be more efficient than smaller ones.

The three land-fragmentation indicators were found to be statistically significant in most cases and had the anticipated signs. The positive effect of the number of plots on TE implies that the variation effect exceeded the management effect. This confirms the findings of Sherlund et al. [26] that TE is higher for farmers who cultivate more rice plots. Likewise, with other variables remaining constant, an increase in average plot size will cause an increase in TE for both early rice and one-season rice. In early rice the effect of distance was statistically significant and had the expected sign.

The two soil-quality indicators had the expected signs in the early-rice model, but only the indicator for good soil quality had a statistically significant effect at 10% level on TE. This finding implies that a poorer soil quality may create obstacles in technology application. Furthermore, we found that credit availability and savings can improve technical efficiency, especially in one-season rice, indicating that they can reduce problems with timely availability of inputs. When farms had their own oxen, they could improve one-season rice production through more timely land preparation, as expected.

Table 5
Overall technical efficiency (TE) scores for the three rice production systems.

TE scores	Early rice	One-season rice	Late rice
Max	0.98	0.98	0.97
Min	0.48	0.30	0.70
Mean	0.91	0.80	0.89
SD	0.08	0.15	0.04

4.3. Technical efficiency scores

Table 5 shows that the average TE for the sample was 0.91, 0.80 and 0.89 for early rice, one-season rice and late rice, respectively. This agrees closely with the results of Tian and Wan [33], which were 0.95, 0.95, 0.94 and 0.91 for Indica early, late and mid-rice and Japonica rice in China, respectively; with the results of Xu and Jeffrey [34], which were 0.94, 0.91 and 0.87 for conventional rice in south, central and north China, respectively, and 0.85, 0.78 and 0.74 for hybrid rice in the same regions, and with the result of Feng [8], which was 0.82 for a sub-sample of 52 households of our dataset. Studies for other cereals and cropping as a whole, however, generally found much lower TE levels (see Table 5 in Chen et al. [32].

Table 6 shows that 32% of the respondents in early-rice production operated at an efficiency level higher than 95%. For one-season rice production, 13% of the respondents exceeded that level, but only one among the 261 late-rice producers reached this level. On the other hand, 24% of the one-season rice producers operated at a technical efficiency level below 70%, whereas only 3% of the early-rice producers and only one later-rice producer had a technical efficiency level below 70%.

The TE scores suggest that on average the respondents were able to obtain 80–90% of potential output by using the given mixture of production inputs. It also implies that in the short run, there is limited room for improving rice yields for households with efficiency levels close to or higher than the average value. However, households with low efficiency levels can still realize a substantial increase in TE, particularly in one-season rice production, e.g., by improving education, increasing average plot size, and improving soil quality, such

Table 6
Distribution of technical efficiency scores for the three rice production systems.

Rice type		Technical efficiency scores						
		<0.50	0.50–0.60	0.60–0.70	0.70–0.80	0.80–0.90	0.90–0.95	>0.95
Early rice	No. of cases	1	2	5	17	48	107	84
	%	0.38	0.76	1.89	6.44	18.18	40.53	31.82
One-season rice	No. of cases	13	12	24	35	56	40	26
	%	6.31	5.83	11.65	16.99	27.18	19.42	12.62
Late rice	No. of cases	0	0	1	5	143	111	1
	%	0.00	0.00	0.38	1.92	54.79	42.53	0.38

that their efficiency can approach that of the best performing farms.

5. Concluding remarks

Rice farming is an important income-generating activity and a major factor in attaining food self-sufficiency in large parts of rural China. Increasing rice productivity is therefore of crucial importance for improving the livelihoods of households living in China's major rice-producing areas. However, the relatively high degree of land fragmentation may constitute an important bottleneck in this respect.

This study used detailed household, crop- and plot-level data to investigate the impact of land fragmentation and other potential obstacles on rice producer's technical efficiency in a major rice-growing area in South-East China. A one-stage method was applied to estimate a stochastic frontier model in which the traditional agricultural inputs and socio-environmental factors confronted by farmers were estimated simultaneously.

Results show that there were statistically significant differences in technology levels among the villages studied. The most remote village in our sample had the lowest level of technology, whereas the level of technology was highest in the village with best market access. Within villages, however, the average technical efficiency of rice farmers was 80–90%, suggesting that improvement in rice production will be limited under existing technologies. New technologies have to be introduced to raise rice productivity in the long run.

Land fragmentation was found to be one of the significant factors explaining TE differentials among farmers in the research areas. A larger average plot size increased TE. Given plot size, an increase in the number of plots also had a statistically significant positive impact on TE, indicating that positive variation effects dominate over negative management effects. The distance between homestead and plots was observed to have a statistically significant negative impact on TE in early-rice production, implying that there may be significant gains from reducing travel time to spatially dispersed plots and from reducing management inconveniences. Increasing average plot size, reducing the distance to the plots and a better integrated management of rice fields (poor soil quality is found to create obstacles for technology application) could be effective ways to increase TE and therefore increase rice productivity and improve the livelihoods of rural households in China's major rice-growing regions in the short term.

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