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Does land perform well for corn planting? An empirical study on land use efficiency in China

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ABSTRACT

To assess land quality for cropping, this study developed a land performance indicator (LPI), namely efficiency of total land productivity potential (TLPP), by incorporating the heterogeneity of land quality for individual agricultural production units when evaluating the performance of land for corn planting, using stochastic frontier analysis. Without taking into account land quality, the technical efficiency (TE) of corn production cannot be reasonably compared across regions because the variation in land quality is significant. The estimated mean TE was 0.77, which illustrates that there is still potential to increase output by 23%, without increasing inputs, if all agricultural production units emulate the best performing production units. The results demonstrated that the mean LPI was 0.273, with a maximum value of 1.0, implying that a large gap exists between the minimum optimum use of TLPP and observed TLPP. This finding indicates that corn planting units can achieve the same outputs with less land inputs through improving the land productivity per unit. The results also revealed that operational units with greater farm area are likely to be more efficient than with those with a smaller area, which suggests that enlarging farm area and promoting household cooperation and joint management practices are imperative to achieve agricultural modernization, enhance the competitiveness of China's agricultural production in the global market, and effectively disengage labor from agricultural production and transfer the resulting surplus labor to cities.

1. Introduction

China's future agricultural development will pay increasing attention to food nutrition, food safety, efficiency, and effectiveness, according to the 13th Five Year Plan (Long et al., 2016; Long, 2014a; Brødsgaard, 2016; Jin et al., 2016). This period is critical for transformation and reconstruction of China's agricultural development, and sustainable use of the land resource and ensuring food safety will be keys to development. Corn planting has played an important role in China's food system because the area planted and output of corn increased dramatically since 1940s, which makes corn surpassed rice to become the largest single crop produced in China (Gale et al., 2014). Estimating the productivity and technical efficiency (TE) of agricultural corn planting by regarding land performance as a primary input will consequently play an essential role in China's agricultural transformation and development.

Area of cultivated land is indisputably a necessary input for assessing agricultural production efficiency. Although it is frequently reported that there is inverse relationship between farm size and yield per unit (Feder, 1985), agricultural productivity and efficiency analysis regarding farm size continues (Carter, 1984; Feder, 1985; Jayne et al., 2016; Mellor and Malik, 2016; Sheng et al., 2016). Almost all the literature to date focuses on the effect of farm size on general grain production or agricultural production, while there is a lack of research examining the relationship between corn planting efficiency and farm size for China's corn farmers from an economic perspective. In this paper, we analyze the TE and productivity of different farm sizes: small (individual households), medium-sized (family farms), and large (major cooperatives).

Apart from farm size, land quality should be considered when

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planning to increase agricultural technical efficiency and agricultural productivity. Many studies have used the area of cultivated land (i.e., farm size) available to a household as one of the primary inputs (Battese, 1992; Lansink et al., 2002; Pascual, 2005; Brümmer et al., 2006; Chen et al., 2009; Zhang and Brümmer, 2011; Asante et al., 2014). However, it is important (although difficult) to incorporate the heterogeneity of land quality as influenced by soil nutrients, soil type, or soil conservation when evaluating land performance in corn planting (Latruffe et al., 2005; Hoang and Alauddin, 2012; Marchand and Guo, 2012; Rao et al., 2012). Without taking into account land quality for each individual agricultural production unit, the TE for corn planting cannot be properly compared across regions because the variation in land quality is significant.

Besides farm size and land quality, some other elements also affect the technical efficiency of agricultural production. For example, Bayacag and Rola (2016) examined whether slope affected soil quality and thus had an influence on agricultural production, while Watkins et al. (2014) investigated whether an area with flat terrain needed less inputs for agricultural production and thus had higher production efficiency. Tang et al. (2015) studied whether improving farmers' income would promote agricultural production. Deininger et al. (2012) considered whether rental land would increase farmers' income and thus increase agricultural production efficiency, and Huang et al. (2017) found renting-in grassland improved the technical efficiency significantly.

To investigate the effect of land quality on productivity, in this study we developed a land performance indicator (LPI), namely the efficiency of total land productivity potential (TLPP), defined as the ratio of the minimum feasible TLPP needed for corn planting with the same output to the observed total cultivated land productivity, conditional on observed levels of the other inputs and outputs (Fig. 1). In this case, the smaller the LPI, the greater the input of the observed TLPP compared with the minimum feasible TLPP. Consequently, a small value of LPI could indicate over-use of the TLPP, which is generated as the product of cultivated land area and productivity per unit.

The overall objective of this research was to quantitatively evaluate the performance of the land resource (both area and quality) by treating it as an input for corn planting, in order to inform sustainable land policy in an era of agricultural transformation and development. The remainder of the paper is structured as follows. We describe the theoretical model in Section 2 and the study area and data in Section 3. The empirical model specification and estimation strategy are presented in Section 4. The results of the study are illustrated and discussed in section 5, and the conclusions of the study are presented in Section 6.

2. Theoretical model

To estimate the TE and values of LPI for agricultural corn planting, we developed a corn planting function incorporating TLPP as one of the inputs. Corn planting households use inputs x to produce y (Aigner et al., 1977). For a given i^{th} production unit, we devised a one-output multi-input production function:

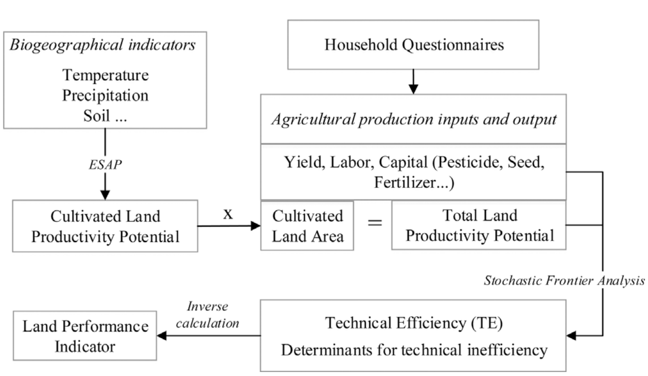

Fig. 1. The general framework of this study.

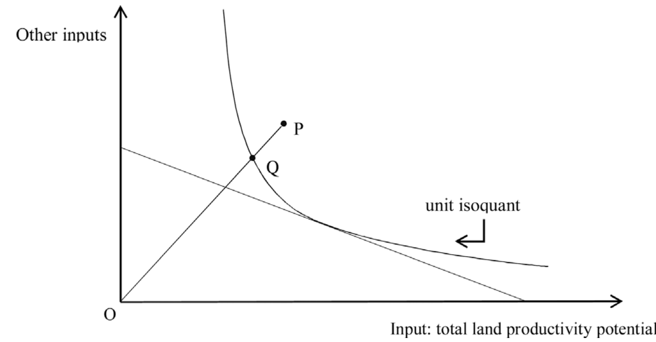

Fig. 2. Description of technical efficiency.

$$y_i = f(x_i; \beta)\exp(v_i - u_i) \quad i = 1,2,\cdots,N. \tag{1}$$

The translog functional form is specified as:

$$\ln(y_i) = \beta_0 + \sum_{k=1}^{3} \beta_k lnx_{ik} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{kl} lnx_{ik} lnx_{il} + \varepsilon_i;\ \varepsilon_i = v_i - u_i \tag{2}$$

where the term v_i is set to capture noise, $v_i \sim$ i.i.d. $N(0, \sigma_v^2)$ and the term u_i is set to be the technical inefficiency term, $u_i \sim N(\mu_i, \sigma_u^2)^+, i = 1, 2, \ldots, N$. The mean μ_i is defined as the technical inefficiency model:

$$\mu_i = \tau_0 + z_i \times \tau_i \tag{3}$$

where z_i is a vector of explanatory variables (including input variables) associated with the technical inefficiency, τ_0 is a constant term in the technical inefficiency model, and τ_i is a vector of unknown parameter to be estimated (Coelli and Battese, 1996; Huang, 2015). We used Maximum Likelihood Estimation (MLE) to estimate the parameters. The unit isoquant of the fully efficient producer (represented in Fig. 2) permits the measurement of TE. Suppose the grain producer uses TLPP and other inputs to produce corn, operating at point P, the TE of a grain producer can be expressed by the ratio:

$$\text{TE} = \frac{\text{OQ}}{\text{OP}} \tag{4}$$

where TE takes a value between zero and one, and the technical inefficiency value equals one minus the TE value. A technical efficiency value of one implies the grain producer is fully technically efficient. For example, the point Q (Fig. 2) is technically efficient because it lies on the efficient isoquant.

The LPI, which is termed the efficiency of TLPP, is defined as the ratio of the minimum feasible TLPP needed for corn planting with the same output to the observed TLPP, conditional on observed levels of input labor and capital, and corn output (Reinhard et al., 2002; Huang et al., 2016):

$$LPI_i = \frac{Min.\ \ total\ land\ productivity\ potential}{Observed\ total\ land\ productivity\ potential} \tag{5}$$

3. Study area and data

3.1. Study area

We selected Shandong Province and Heilongjiang Province as case study areas, because both are regarded as key 'breadbaskets' for China. Heilongjiang Province is one of the nation's commercial corn planting bases and has high potential for agricultural development as a result of its high level of mechanization and huge available cultivated land area. Shandong Province has good conditions for corn planting, including temperature, sunlight hours, and water availability. The locations of the study areas and of the sampled villages are presented in Fig. 3. We took into account the heterogeneity of land productivity per unit for these two spatially non-adjacent provinces while developing estimates of both productivity and TE, which provided an effective means of comparing the planted land across the two provinces.

3.2. Input and output data

The socio-economic data serving as model specifications in this paper were drawn from field surveys and questionnaires surveys performed in July 2015 in Shandong Province and Heilongjiang Province, organized by the Center for Chinese Agricultural Policy of the Chinese Academy of Sciences. A stratified random sampling method was used for sampling villages (illustrated by the red points in Fig. 3). The weighted average ranking score for each county was calculated according to the ranking of corn planting each year, to ensure that the selected counties were representative of the sampled province in terms of economic development and grain harvest. For Shandong Province, 13 out of 17 prefecture cities and one county from each prefecture city were picked at random and then two towns from each county and one village from each town were picked at random. Since the diversity of landscape among cities for Heilongjiang Province is not as high as for Shandong Province, we halved the sampling percentage for Heilongjiang cities ($0.5 \times 13 \times 13/17 = 4.97$) and therefore, five out of 13 prefectural cities and two counties from each prefecture city were picked at random, and then one town from each county and one village from each town were picked at random. Within the villages, sampling units (on average, five to eight individual households and one to two family farms/cooperatives) were sampled randomly. In total, for both provinces, we selected 284 sampling farms from 34 villages, including individual households, family farms,[1] and cooperatives. Of these 284 sampled farms, 234 are located in Shandong and 50 in Heilongjiang.

The analysis was based on a one-output multi-input production function for stochastic frontier analysis. The output in the production function was annual output of corn per sampling unit (individual household, family farm, and farmer cooperative), measured in kilograms. Classic inputs were aggregated into three categories (labor, capital, and TLPP). Labor was defined as consisting of family labor and employed labor, measured by a person working eight hours per day. Capital was defined as consisting of the costs of fertilizer, seed, pesticides, and renting production machinery. Land is a key variable and was defined as the product of cultivated land area and land productivity potential. Land as a variable and the heterogeneity of land productivity are described in detail in the next section. We selected terrain (topographical slope), the area rented by the selected farm from other households, and the total net revenue from planting corn as the sample unit characteristic variables. A statistical description of the variables is presented in Table 1.

3.3. Total land productivity potential data

The TLPP data were generated using the estimation system of agricultural productivity (ESAP), which was developed by Deng et al. (2006) and adapted from the agro-ecological zone (AEZ) model. The principle of this estimation system is to evaluate cultivated land productivity potential through correcting the preliminary results stepwise with the aid of biophysical parameters, such as temperature, precipitation, land cover, and land use. Details about the estimation procedure and a discussion regarding the ESAP and its application can be found in Jiang et al. (2011, 2015). After the stepwise correction, the TLPP indicator can represent the potential amount of grain produced per unit land area. Spatially explicit land productivity potential data, generated using ESAP for Shandong and Heilongjiang provinces in 2015, are displayed in Fig. 4. As can be seen from the diagram, land productivity potential data differ significantly between Shandong and Heilongjiang provinces, confirming the need to incorporate an indicator of heterogeneous land productivity beyond farm size.

4. Empirical model specification and estimation measurement

Empirically, for corn planting in Shandong and Heilongjiang provinces, we set the unlimited functional form for the parametric function as:

$$\ln(y_i) = \beta_0 + \beta_1 lnx_{1i} + \beta_2 lnx_{2i} + \beta_3 lnx_{3i} + \frac{1}{2}\beta_{11}(lnx_{1i})^2 + \frac{1}{2}\beta_{22}(lnx_{2i})^2 + \frac{1}{2}\beta_{33}(lnx_{3i})^2 + \beta_{12} lnx_{1i} lnx_{2i} + \beta_{13} lnx_{1i} lnx_{3i} + \beta_{23} lnx_{2i} lnx_{3i} + v_i - u_i \tag{6}$$

where y denotes the vector of output, here corn output per sampled unit, and x_k is a vector of inputs with x_1 = labor; x_2 = capital, x_3 = TLPP, which is generated as land area multiplied by land productivity potential indicator per unit.

For estimation of the LPI, we assumed that the producer would be most land use efficient when using the minimum feasible coTLPP. The logarithm production frontier of an land use efficient producer is then obtained by replacing the observed x_3 and u_i with $\overline{x}_3$ and $\overline{u_i}$, respectively. The translog production frontier for land use efficient corn planting is then written as:

$$\ln(y_i) = \beta_0 + \beta_1 lnx_{1i} + \beta_2 lnx_{2i} + \beta_3 ln\overline{x}_{3i} + \frac{1}{2}\beta_{11}(lnx_{1i})^2 + \frac{1}{2}\beta_{22}(lnx_{2i})^2 + \frac{1}{2}\beta_{33}(ln\overline{x}_{3i})^2 + \beta_{12} lnx_{1i} lnx_{2i} + \beta_{13} lnx_{1i} ln\overline{x}_{3i} + \beta_{23} lnx_{2i} ln\overline{x}_{3i} + v_i - \overline{u}_i \tag{7}$$

where $\overline{x}_3$ refers to the optimal minimum feasible input of TLPP, which is the amount of TLPP that should be used for full land use efficiency. Letting Eq. (6) be equal to Eq. (7) allowed us to isolate the logarithm of LPI (denoted by Eq. (8)) by using Eq. (9).

$$lnLPI_i = ln\frac{\overline{x}_{3\,i}}{x_{3\,i}} = ln\overline{x}_{3\,i} - lnx_{3\,i} \tag{8}$$

$$\frac{1}{2}\beta_{33}[(ln\overline{x}_{3\,i})^2 - (lnx_{3\,i})^2] + \sum_{k=1}^{2} \beta_{k3} lnx_{ki}[ln\overline{x}_{3\,i} - lnx_{3\,i}] + \beta_3[ln\overline{x}_{3\,i} - lnx_{3\,i}] + u_i = 0 \tag{9}$$

Letting $a = \frac{1}{2}\beta_{33}$, $b = \beta_3 + \sum_{k=1}^{2} \beta_{k3} lnx_{k3} + \beta_{33} lnx_3$, $c = -\overline{u_i} + u_i$, and let $\overline{u_i} = 0$ by assuming that households would operate technically efficiently if they operated their land use efficiently, an assumption consistent with previous findings in environmental efficiency analysis, we can therefore obtain the LPI from:

$$lnLPI_i = ln\overline{x}_{3\,i} - lnx_{3\,i} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \tag{10}$$

Finally, the LPI of a corn planting household was calculated as$LPI_i = e^{lnLPI_i}$.

The technical inefficiency model is given by Eq. 3, $\mu_i = \tau_0 + z_i \times \tau_i$, where z is a vector of explanatory variables associated with the technical inefficiency. In this study, we used the categorical variable of terrain (*terrain*), the area rented from other household (*inarea*), and total net revenue from planting corn (*netrevenue*), and first-order

[1] A family farm is an agricultural production unit and business agent. The dominant labors for agricultural production is family members. The mode of operation for agricultural production is relatively large scale, intensive, and commercialized, and the primary family revenue comes from agricultural production. The concept of the family farm in China was proposed for the first time in 2008, and was subsequently highlighted as an important organizational unit for agricultural production in the "No. 1 document of the central government" in 2013.

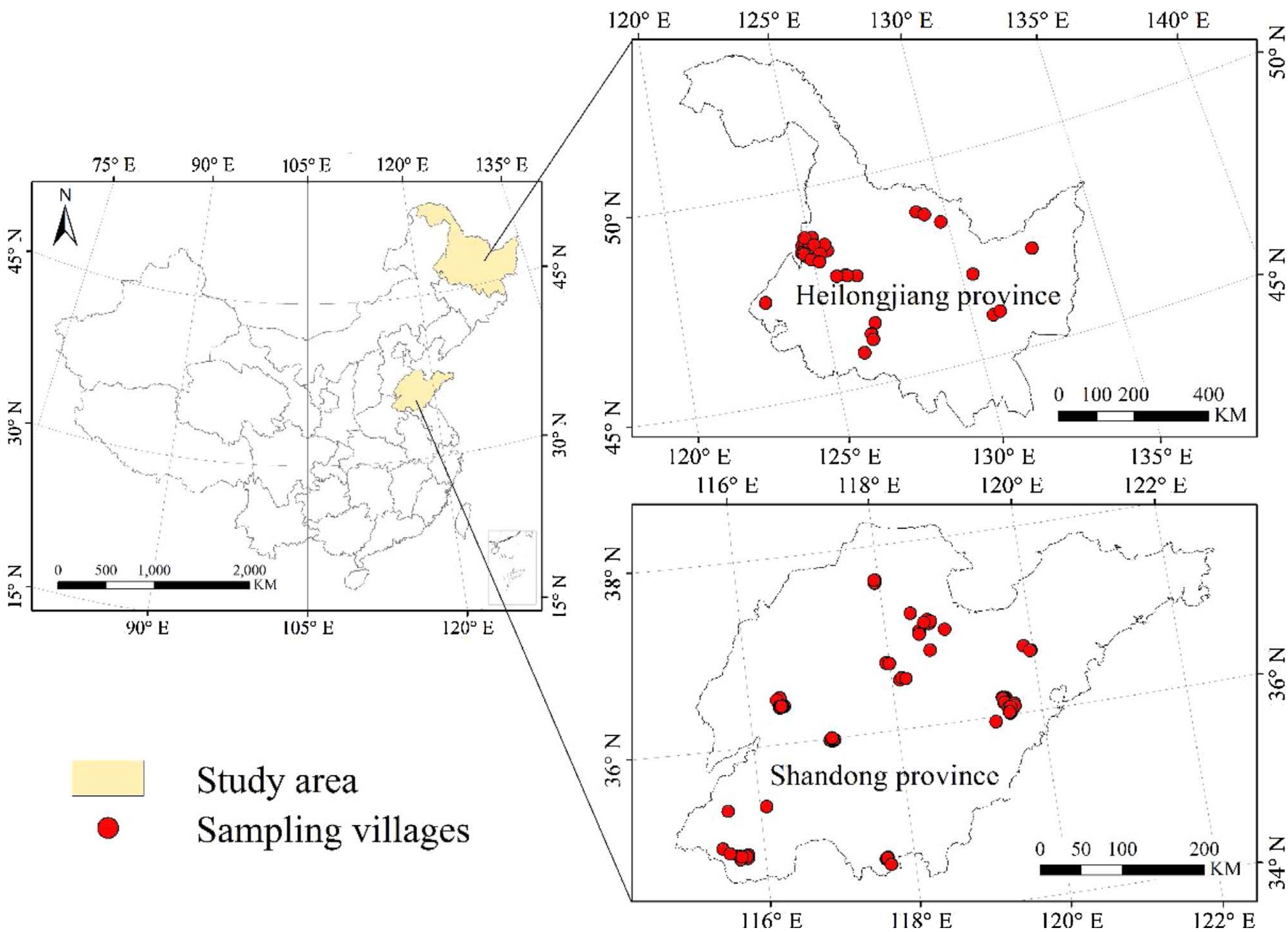

Fig. 3. Location of the study area and distribution of samples.

Table 1
Descriptive statistics on variables in the frontier function and inefficiency model.

Variable	Unit	Symbol	Mean	Std. Dev.
Corn output	10^3 kg	*output*	115	427
Capital	10^3 yuan	*capital*	38.56	124.79
Labor (working h, 8 h/day)	day	*labor*	150.0	628.9
Total land productivity potential (TLPP)	ton	*TLPP*	696.32	3537.33
Terrain (1 = plain, 2 = hill, 3 = mountain)	–	*terrain*	1.25	1.0
Area rented from other households	mu	*inarea*	83.4	341.0
Total net revenue from planting corn	10^3yuan	*netrevenue*	52.83	285.59

variables from the production function. After estimation of the technical inefficiency model, we subsequently calculated the LPI.

5. Result and discussion

We first used the MLE method to estimate the stochastic frontier in combination with the technical inefficiency model and then calculated the LPI. The general-to-specific modeling method (Hendry, 2000) was used in variable selection. We began by running a model that included all control variables, and then we dropped the least significant variable and ran the model again. This procedure was repeated until only variables that were significant enough to pass likelihood ratio tests at 10% level remained. The final model specifications are listed in model 3.

5.1. Stochastic production function estimates

Maximum likelihood estimates of the stochastic frontier are presented in Table 2, in which model 1 the results using the Cobb-Douglass production function, while model 2 represents the results of the Translog production function without setting the technical inefficiency model and model 3 shows the results of the Translog production function associated with the technical inefficiency model. The overall qualities of model 3 seemed satisfactory according to likelihood ratio tests, which showed that model 3 is preferable to model 2. This indicated that we should consider the determinants of technical inefficiency using the technical inefficiency model.

As the output and input variables were divided by their respective sample means, the estimated first-order parameters of the translog frontier can be interpreted as partial elasticities at the sample mean (Huang et al., 2016, 2017). All the first-order coefficients of the inputs had the expected sign. In particular, the coefficients of input of capital and TLPP were significantly different from zero at the 1% level. In terms of the magnitude of elasticity at the sample mean, the most important input for corn planting discovered here was capital. The elasticity with respect to capital was estimated to be 0.878 at the 1% significance level, implying that the change in capital represents 87.8% of the total change at the sample mean. The elasticity with respect to TLPP was estimated to be 0.114 at the 1% significance level.

5.2. Technical inefficiency model estimates and technical efficiency (TE)

Technical inefficiency exists in the households' corn planting operations.The determinants of variations in the TE of corn planting households were estimated using the technical inefficiency model

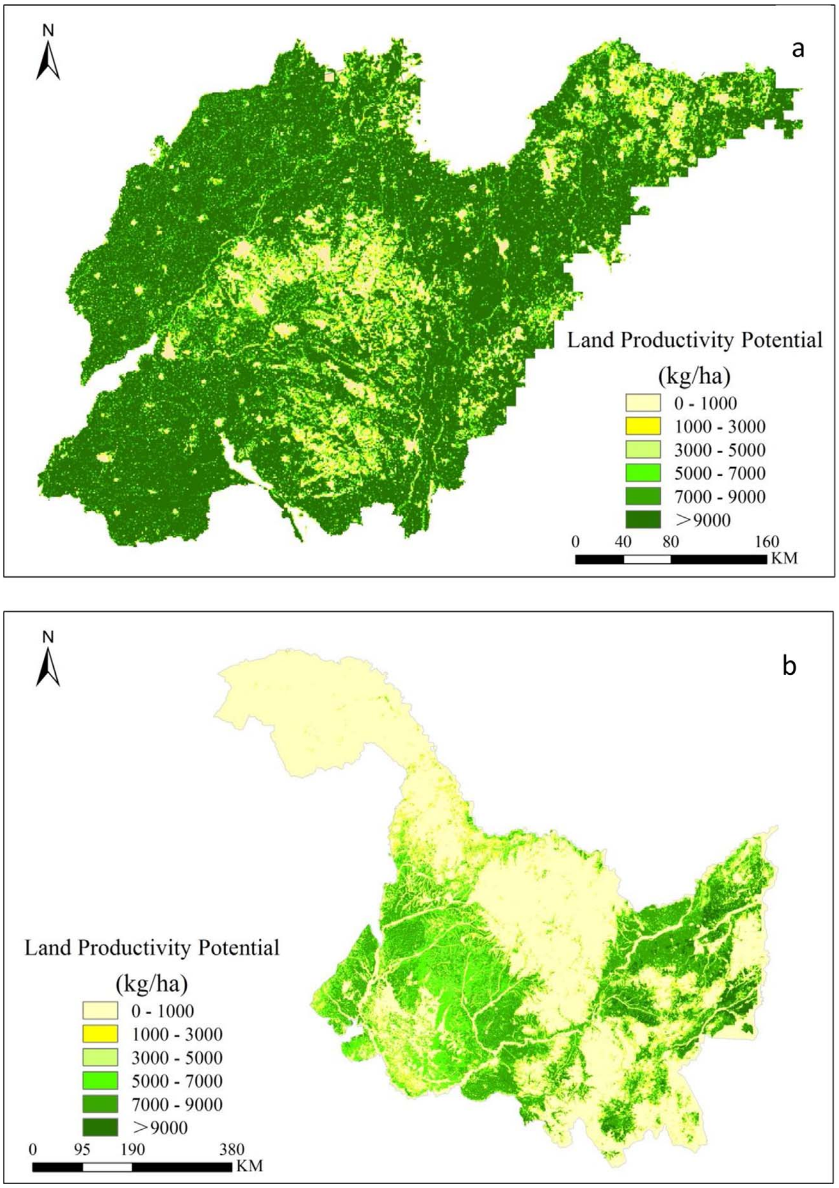

Fig. 4. Spatially explicit total land productivity potential (TLPP) results generated from ESAP for a) Shandong Province and b) Heilongjiang Province. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(middle part of Table 2). Because technical inefficiency is the dependent variable in the technical inefficiency model, a negative parameter coefficient for the variables indicates a negative effect on technical inefficiency and, conversely, a positive effect on TE.

In the technical inefficiency model, *capital*, *labor*, and *inarea* were estimated to be statistically significant. It is interesting to see that the coefficients for capital and labor are different, which means that there is a negative relationship between capital and technical efficiency, but a positive relationship between labor and technical efficiency. Increasing labor input would be of benefit not only to production level, but also to technical efficiency individually. *Inarea* was found to be statistically significant in relation to technical inefficiency. The coefficient of *inarea* was estimated to be -0.021, statistically significant at least at a level of 10%, indicating that the more crop land the household rents from others, the more technically efficient its corn planting will be. After estimating the stochastic frontier function and technical inefficiency model, we calculated each household's TE. The average estimated TE for corn planting households in model 3 was 0.77, indicating that these corn planting households could, on average, increase corn output by 23%, given the present status of technology and the current level of inputs, by adopting the practices of the best performing households. On average, it was found that corn planting households in Shandong Province operate more efficiently than those in Heilongjiang Province, with the average TE for Shandong households being 0.777 and that for Heilongjiang households being 0.737 (Table 3).

The distribution of TE values in the two provinces showed that 47.02% of Shandong households had a TE $\geq$ 0.95, compared with 42% of Heilongjiang households. Moreover, 11.54% of Shandong households had an efficiency scores of $<$ 0.95 and $\geq$0.90, compared with 4% of Heilongjiang households, and 26.50% of Shandong households operated with a TE of $<$ 0.80, compared with 38% of Heilongjiang households In short, households were more likely to show higher TE in Shandong Province than in Heilongjiang Province.

5.3. Analysis of the land performance indicator (LPI)

The LPI is the ratio of the minimum optimum input of TLPP needed for corn planting with the same output to the observed TLPP. The lower the LPI, the greater the observed TLPP compared with the minimum feasible TLPP. Thus, a low LPI value could indicate over-use of land, in terms of either land area (farm size) or land productivity per unit. The mean LPI was found to be 0.273, with a maximum value of 1.00

Table 2
Estimation results for the production function and technical inefficiency model.

Parameter	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Stochastic production frontier						
Dependent variable: ln(output)	Model 1		Model 2		Model 3	
ln(*capital*)	0.919***	0.029	0.878***	0.059	0.815***	0.057
ln(*labor*)	0.021	0.027	0.008	0.05	0.005	0.033
ln(*TLPP*)	0.053***	0.019	0.114***	0.038	0.111***	0.031
0.5 × [ln(capital)]^2			0.175***	0.047	0.171***	0.038
0.5 × [ln(labor)]^2			0.103***	0.037	0.051*	0.026
0.5 × [ln(TLPP)]^2			0.033	0.024	0.049*	0.022
ln(*capital*) × ln(*labor*)			−0.139***	0.033	−0.097***	0.022
ln(*capital*) × ln(*TLPP*)			−0.053	0.028	−0.069**	0.027
ln(*labor*) × ln(*TLPP*)			0.03	0.018	0.029*	0.014
Constant	0.438***	0.056	0.443***	0.057	0.089	0.066
lnsig2v						
Constant	−2.292***	0.204	−2.906***	0.31	−2.667***	0.258
Technical inefficiency model						
Dependent variable: technical inefficiency relevant						
capital					2.491*	1.117
labor					−1.173*	0.537
TLPP					−0.535	0.785
terrain					0.835	0.585
inarea					−0.021*	0.009
netrevenue					−0.0002	0
Constant			−0.754***	0.166	−1.443	0.808
Statistics						
Observations	284		284		284	
Likelihood ratio	−197.370		−180.102		−95.012	
Chi-square	3871.260		4575.610		2671.800	
AIC	406.740		384.205		226.024	

* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 3
Summary of results for estimated technical efficiency (TE) and land performance indicator (LPI) by province.

Variables	Mean	Std. Dev.	Min.	Max.
TE				
Shandong Province	0.777	0.208	0.158	1.000
Heilongjiang Province	0.737	0.282	0.158	1.000
Overall	0.770	0.222	0.158	1.000
LPI				
Shandong Province	0.251	0.363	0.000	1.000
Heilongjiang Province	0.377	0.438	0.001	1.000
Overall	0.273	0.379	0.000	1.000

(Table 3), implying that there is a large gap between the minimum optimum use of cultivated land TLPP and observed land productivity, which could mean that either land area or land productivity per unit of cultivated land is overused.

We statistically describe the correlation between farm size, the LPI, and the technical efficiencies in Table 4. The distribution of TE with respect to farm size showed that the two groups of greater farm size were the most efficient operational units. In other words, households that operated farms more than 5 ha in area were more technically efficient than households that operated farms less than or equal to 5 ha. Given that smaller farms of current individual households have lower TE, enlarging the size of farms by promoting cooperative production or other management practices might be imperative to increase TE and thus achieve agricultural modernization. However, when taking into account both LPI and farm size, the highest TE score was 1.000 for a combination of ‘5 < farm size ≤ 10 & 25% < LPI ≤ 50%’ and ‘5 < farm size ≤ 10 & 75% < LPI ≤ 100%’, followed by 0.999 for a combination of ‘farm size > 10 & 25% < LPI ≤ 50%’. This means that farm size is not the only solution when attempting to increase the TE of corn planting. Thus instead of only the single aspect of farm size, multiple factors such as the degree of urbanization and the level of local social service systems should also be considered.

Table 4
Technical efficiency values (percentage of household in brackets) for different farm size and land performance indicator (LPI) classes.

Farm size (ha)	LPI group				Total
	0–25%	25%–50%	50%–75%	75%–100%	
Farm size ≤ 1	0.674 (13.38%)	0.624 (18.66%)	0.705 (14.44%)	0.672 (14.79%)	0.666 (61.27%)
1 < farm size ≤ 5	0.956 (5.63%)	0.886 (2.46%)	0.840 (3.87%)	0.863 (5.28%)	0.891 (17.25%)
5 < farm size ≤ 10	0.985 (3.52%)	1.000 (1.06%)	0.998 (1.41%)	1.000 (1.41%)	0.992 (7.39%)
Farm size > 10	0.975 (2.46%)	0.999 (2.82%)	0.911 (5.28%)	0.997 (3.52%)	0.961 (14.08%)
Total	0.811 (25.00%)	0.708 (25.00%)	0.786 (25.00%)	0.777 (25.00%)	0.770 (100%)

Note: Values in brackets are percentages of household.

5.4. Relevant policy discussion

The results of our empirical study confirm land productivity as an important input for agricultural production. The total input, output, cash revenue, and net profit for China’s agricultural production from 2002 to 2013 (Fig. 5) reveal a distinct trend of increasing output, but decreasing farm income. The policy shift from “storing food in the granary” to “storing food in the land” (in Chinese “*cang liang yu tu*”) aims to mitigate the distortion of food prices to some degree. The objectives of this policy are to alleviate the pressure on grain storage, reverse the trend of decreasing income for farmers, and promote

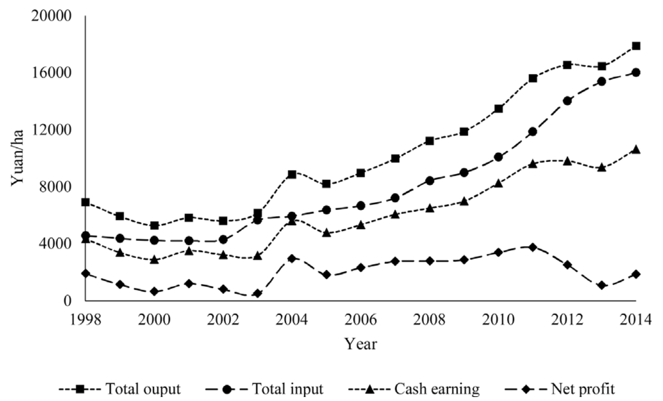

Fig. 5. Total input, output, cash earnings, and net profit for China's corn planting, 2002–2014.

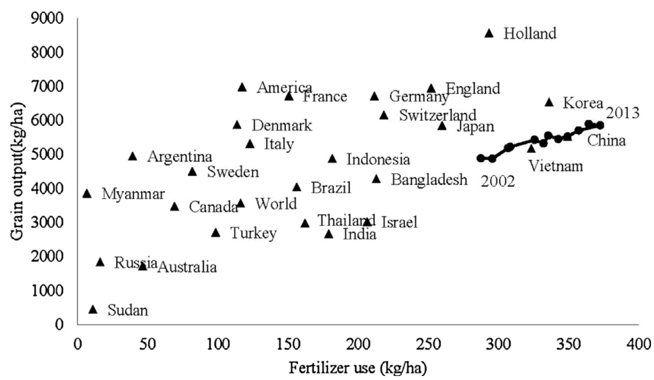

Fig. 6. Relationship between grain yield and fertilizer input for selected countries.

sustainable cultivated land use and development. Regarding this point, our empirical study showed that it is possible for agricultural production units to achieve greater outputs using unchanged input of TLPP through learning from the best performing households in terms of technical efficiency. This finding corroborates the rationality and potential of the "storing food in the land" policy, which provides a suitable strategy for increasing farmers' income.

The fertile cultivated land has been encroached on, and replaced by reclaimed land with relatively low quality (Liu et al., 2014a,b; Dong et al., 2015). High yields from China's agriculture have always come at the cost of high levels of input (such as fertilizers and pesticides), as demonstrated by the relationship between fertilizer input and grain yield in China from 2002 to 2013 (black line in Fig. 6). Fig. 6 depicts the relationship between fertilizer input and grain yield for other selected countries in 2013. Taking Japan as an example, China reached the same amount of yield as Japan in 2013, but China's fertilizer input per hectare was over 100 kg more than that of Japan. Broadly speaking, through their history and trend of agricultural development, developed countries have experienced a pathway that shifted from initially yield-targeted production to synergetic development which balanced agricultural production and eco-environment protection (Carvalho, 2006). Finally, improvements in land resource efficiency might be achieved not only through increasing production efficiency, but also through minimizing the length of the supply chain, reducing consumer wastes and losses, and increasing the consumption efficiency (Van den Berg et al., 2016).

6. Conclusion

Previous studies have found that farm size is one of the necessary inputs for assessing land use efficiency. However, it is a challenge to incorporate heterogeneity in land quality per unit when evaluating the performance of land in e.g., corn planting. In this study, we sought to fill this research gap by estimating the production function and technical inefficiency model, on the basis of which we calculated values of land performance indicator (LPI).

The results showed that the mean technical efficiency (TE) of the farms studied was 0.77, which means that output could be increased by 23% without a change of inputs if all agricultural production units learned from the best performing production units (i.e., those with the highest levels of TE). The results also showed that the mean LPI was 0.273, with a maximum value of 1.0, indicating that there is a large gap between the minimum optimum use of cultivated land TLPP and the observed TLPP. This indicates in turn that the agricultural production units studied can achieve the same outputs with less land inputs, e.g. the agricultural output can be increase not necessary by increasing the land area size, but more attention might be paid on how to improve the cultivated land productivity per unit. This finding corroborates the rationality and potential of the "storing food in the land" policy.

However, "storing food in the land" is only a guiding policy that addresses the direction of development in China. In practical terms, implementing this policy first requires overall design and planning for entire nation, followed by engineering solutions with the aid of scientific evaluation of current land productivity and its potential increase (Liu et al., 2014a,b). Given the condition of ensuring food security, regionally differentiated strategies with specific targets should be promoted, such as regional fallow and soil fertility improvement measures. It is crucial to combine management and policy strategies with engineering solutions, although measures of this type have often been ignored (Lu et al., 2013; Long, 2014b; Yan et al., 2014, 2016).

The results of our empirical study confirmed land productivity as an important input for agricultural production. We suggest that policy makers pay close attention to the gains and losses in cultivated land productivity, rather than simply changes in cultivated land area, although this may be challenging in practice. Only when policy strategies, engineering solutions, and consumption behavior are tightly combined can sustainable and efficient land resource usage be achieved. Bearing this in mind, the major findings of this innovative empirical study provide a better understanding of agricultural transformation and development in China from the perspective of land performance.

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