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Environmental Efficiency Analysis of China's Vegetable Production

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Objective To analyze and estimate the environmental efficiency of China's vegetable production. **Methods** The stochastic translog frontier model was used to estimate the technical efficiency of vegetable production. Based on the estimated frontier and technical inefficiency levels, we used the method developed by Reinhard, *et al.*[1] to estimate the environmental efficiency. Pesticide and chemical fertilizer inputs were treated as environmentally detrimental inputs. **Results** From estimated results, the mean environmental efficiency for pesticide input was 69.7%, indicating a great potential for reducing pesticide use in China's vegetable production. In addition, substitution and output elasticities for vegetable farms were estimated to provide farmers with helpful information on how to reallocate input resources and improve efficiency. **Conclusion** There exists a great potential for reducing pesticide use in China's vegetable production.

Key words: Vegetable production; Stochastic translog frontier; Environmental efficiency; Elasticities

INTRODUCTION

For a considerably long period of time before 1980s, production efficiency in China was low due to its planned economy. Food supply was in a constant state of shortage due to limited investment and backward science and technology. Thus the basic policy for the Chinese government in this period was to stimulate all possible forces to increase output and solve the food security problem over the country. As a result, from 1960 to 1980, China's agricultural productivity was increased due to technological developments and increased use of pesticides and chemical fertilizers. On the other hand, in this period, the Chinese government made practically no effort to promote environmental protection, sustainable production and consumption so as to provide safe food and a healthy environment. Therefore, in this period in China, pesticides used to control insects and diseases in agricultural sector were applied primarily based on their effects rather than on their impacts on the environment. In the Yangtse River area, vegetable growers used about 2-3 kg of chemical pesticides for every 667 square meters per farming season. Some of these growers even used 5 kg of pesticides for every 667 square meters per farming season. Moreover, in the northern area of China, for example in Beijing, the vegetable growers applied over 9 kg of pesticides for every 667 square meters per farming season. In the Xiamen agricultural area of south China, the total load of pesticides on agricultural soil was 27 kg/ha on average. Given such excessive use of pesticides, some environmental problems are very severe in China's agricultural sector. Pesticide residues have led to widespread health risks to the public in this country for a long time. In 2003, in Nanjing, a city in the east of China, 30.36% of 56 vegetable samples contained over-tolerance pesticide residues in a survey by the local Product Quality Monitoring Bureau. In another survey by the Product Quality Monitoring Bureau of China in 2001, of the 181 domestic surveillance samples, about 47.5% had over-tolerance residues.

In fact, other than the pesticide residues contained in the vegetable products, the environmental problems created by the pesticide pollution also include other factors such as the leaching of pesticides into the surface and ground water, which may endanger plant and fish life. Agricultural production depends on the availability of adequate water. However, pesticides and chemical fertilizers can affect water quality when man-made chemicals from fertilizers and pesticides leach through the soil into groundwater, or when this substance enters

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surface water in runoff from farmland. Improper handling of pesticides can lead to spills and leaks. Presently, pesticides are found in surface water and groundwater in most areas of China where they are used. The residues of chemical fertilizers and pesticides can make soil and water less suitable for future production in the long run. Therefore, water and soil pollution due to excessive use of fertilizers and pesticides in vast rural areas of China is a severe issue. In addition, excessive pesticide use in agricultural production has also an impact on natural biodiversity. And now, Chinese scientists are concerned with such impact on natural ecological system. Furthermore, the build-up of herbicide and insecticide tolerance in certain weed and insect species resulting from successive use of pesticides and herbicides may impair their effect in agricultural production. As a result, since pesticide and other inputs cause many severe environmental problems in agriculture, sustainable development of China's agriculture has been threatened.

In addition to the above issues induced by environmental problems in China's agricultural system, it is important to maintain a high level of consumer confidence in the quality, safety, and production of China's vegetable food for creating a favorable business climate, and integrating sustainable development principles into China's vegetable production policies. Therefore, changes are necessary in production practices as a result of increased demand, globalization, and international market pressures. Facing these problems, China is increasingly aware of the impact of agricultural practices on environmental and human health. The Chinese government and vegetable growers are becoming more concerned about how to control the impact of their activities, products, and services on the environment. Farmers in this country are feeling the pressure to change their production practices and to meet new consumer demands when the public attention has shifted to the environmental and human health effects of pesticide use.

However, the environmental problems associated with agriculture can not be solved easily and measures of reducing environmental risks should be implemented by sound decision-making at all levels of authorities concerned. To deal with these problems, farmers have to apply pesticide inputs as efficiently as possible. For a sustainable development, producers must optimize outputs on a relatively fixed land base, while minimizing inputs and environmental impacts. Therefore, a method should be used to improve the economic and environmental performance of China's vegetable growers. However, this strategy should be built on the results of several assessments of the impact of agriculture activities on the environment. Important steps which can be taken by the sector to adopt agricultural practices should be based on the agro-environmental indicators. Therefore, to identify and change practices that contribute to environmental pressures in the agricultural production activities, some environmental indices should be used to identify the problems in farming operations.

MATERIALS

The environmental efficiency was estimated based on econometric production models established with statistically representative samples of farms in China. A set of site-specific data were used to estimate translog production frontier function. The input and output data covered 20 important provinces in China. The sample data of output, value of output and inputs used in this model were cited from “China’ s agricultural input and output collections”. We utilized the data describing the production activities of 377 strongly specialized vegetable farms in China. The main problem in our estimate method to choose independent variables was that we should incorporate all the inputs which might have potential impact on the environment and human health into the data set. In this paper, we chose chemical fertilizer and pesticide inputs as two basic environmentally detrimental variables in China's vegetable production.

The data set was based on the same land unit which was 1 mu (about 677 square-meters). Therefore the land input was not included in our model. Given the nature of vegetable production, large machines could not be widely applied in the vegetable production process. In addition, China's traditional vegetable production method also concentrated on the labor intensive operation. The machine input and expenditure were absent in most China's vegetable farms. As a result, we would not include the machine input in our model.

In the translog production function, we chose five important variables (labor, seed, organic fertilizer, chemical fertilizer, and pesticide). To make all the variables have the same unit, all the data in our model were the values of inputs instead of quantities. The CAIOC supplies two sets of prices for the inputs. We chose the price set based on the local price instead of the national price.

Labor input was measured in the cost of labor for one farming season. The labor price was based on the local level when the production function was estimated. Seed input was an elemental input in China's vegetable production, because the price of vegetable seeds was higher than that of crop seeds in China. The chemical fertilizer and green fertilizer were also included, both of which are essential for vegetables. The pesticide input was treated as the main environmentally detrimental input which had the most important impact on the environment and human health. In addition, the chemical fertilizer was also treated as one of the two environmentally detrimental inputs in the efficiency analysis with two detrimental variables, because the nitrogen pollution mostly came from this man-made chemical. In this paper, because the data set included 8 different vegetable varieties, we used a dummy variable in the model, representing 8 different vegetable varieties. Table 1 depicts some statistical characteristics of data used in the model. The output value (per mu) of individual vegetable farms ranged from 270.98 yuan to 930.066 yuan per mu with an average of 2 388.943 yuan per mu in China. Labor input also varied widely from a minimum of 59.6 yuan to a maximum of 6 535 yuan per mu per season. Such a large gap among labor inputs might be induced by the big difference in the local labor prices or technological development levels in different agricultural areas.

TABLE 1

Summary for Five Inputs

	Output Value	Pesticide	Chemical Fertilizer	Organic Fertilizer	Seed Input	Labor Input
Mean	2 388.943	115.4932	52.97725	101.2687	84.13447	547.6542
Median	2 152.4	90.26	30	83.33	51.855	469.805
Maximum	9 300.66	783.4	550	825	661.36	6535.3
Minimum	270.98	1	0.16	3.6	6.25	59.6
Std. Dev.	1 344.465	96.13291	69.78273	86.23998	88.61251	453.2728

METHODS

In this paper, the environmental efficiency index was used as the agro-environmental indicator in China's vegetable production. At the same time, pursuing environmental efficiency in the vegetable sector may further enhance the sector's capacity of reducing costs, while contribute to good environmental performance. The efficiency associated with pesticide use was estimated through a modeling method. In this study, the method to analyze environmental efficiency developed by Reinhard, *et al.*[1] and stochastic frontier model were used to measure environmental effects with economic parameters to better predict the impacts of our activities on agricultural production. In this method, two fundamental components formed the basis of our modeling approach to measure environmental efficiency. First, the econometric method was used to estimate technical efficiency and parameters using translog production function. Second, we used the method developed by Reinhard, *et al.*[1] to calculate the environmental efficiency index.

According to Farrell[2] the output of the most efficient firm could be defined as the production frontier for all firms. Any firm at full efficiency should be operated at maximum potential output levels, and any deviation from the estimated frontier would be used to measure its inefficiency. Presently, the most popular methods found in the efficiency estimate involved the frontier production function using econometric methods and non-parametric data envelopment analysis(DEA) using mathematical programming techniques. Since DEA was deterministic and non-parametric, a frontier estimated by this technique was believed to be sensitive to stochastic noise in the data. In this paper, the stochastic frontier model was used, and based on the estimated frontier function, the environmental efficiency was calculated.

Generally, the environmental inefficiency was found by comparing the estimated environmental efficiency frontier with observed data set. Because the environmental efficiency analysis was based on the stochastic frontier model which was used to obtain technical efficiency estimates and parameters, we would first discuss it. According to professor Coelli[3], the stochastic frontier model could be written as: $Y_i=F(X_i, \beta)\cdot\exp\{V_i-U_i\}$. In this function, Y is the production level, X is a vector of input, β is a parameter vector, V is a random error term that is assumed to be independently and identically distributed, and U is a nonnegative random error term used to capture technical inefficiency. The U_i is assumed to be independently distributed and thus obtained by truncation of the normal distribution. Therefore, the output oriented technical efficiency could be defined as: $TE=Y_i/[F(X_i, \beta)\cdot\exp\{V_i\}]$ or $TE=\exp\{-U_i\}$.

According to Reinhard, *et al.*[1], because a Cobb-Douglas function could not add any new information in the environmental efficiency analysis, we would use translog production function in this paper. Following the model of Coelli *et al.*[4], a stochastic translog production frontier function was estimated as:

$$LnY_i=\beta_0+\beta_1LnX_1+\beta_2LnX_2+\beta_3LnX_3+\beta_4LnX_4+\beta_5LnX_5+0.5\beta_{11}Ln^2X_1+0.5\beta_{22}Ln^2X_2+0.5\beta_{33}Ln^2X_3+0.5\beta_{44}Ln^2X_4+0.5\beta_{55}Ln^2X_5+\beta_{12}LnX_1LnX_2+\beta_{13}LnX_1LnX_3+\beta_{14}LnX_1LnX_4+\beta_{15}LnX_1LnX_5+\beta_{23}LnX_2LnX_3+\beta_{24}LnX_2LnX_4+\beta_{25}LnX_2LnX_5+\beta_{34}LnX_3LnX_4+\beta_{35}LnX_3LnX_5+\beta_{45}LnX_4LnX_5+(V_i-U_i)\cdots\cdots (1)$$

where Ln denotes the natural logarithm, Y_i is the total value of outputs (RMB) for the i-th farm, X_1 is the labor input of the i-th farm, X_2 is the seed input of the i-th farm, X_3 is the organic fertilizer input (including animal manure and green manure) of the i-th farm, X_4 is the chemical fertilizer input of the i-th farm, X_5 is the pesticide input of the i-th farm.

For each input X_i (i=1, 2, . . ., 5), there was a corresponding output elasticity which was defined as the percentage variation of the i-th vegetable farm's output value for a 1% change in the i-th input factors. For a Cobb-Douglas production function, the estimated parameters were output elasticities themselves. However, for the translog production function in our paper, the output elasticity was different from the estimated parameters, and we calculated the output elasticity by using total differential to approximate the translog function. The deduced function included the input factors, and therefore, under the translog specification, the output elasticity for each input of various vegetable farms actually depended on the relative input levels and estimated parameters. The deduced function:

$$\partial Y/Y=(\partial X_1/X_1)(\beta_1+\beta_{11}LnX_1+\beta_{12}LnX_2+\beta_{13}LnX_3+\beta_{14}LnX_4+\beta_{15}LnX_5)\cdots\cdots (2)$$

In this function, X_1 is used as an example to deduce its output elasticity. The output elasticity of X_1 is equal to "$S_1=\beta_1+\beta_{11}LnX_1+\beta_{12}LnX_2+\beta_{13}LnX_3+\beta_{14}LnX_4+\beta_{15}LnX_5$" in the above function. The output elasticities of other input factors could be calculated using the same method. In this function, if $\beta_{11}=\beta_{12}=\beta_{13}=\beta_{14}=\beta_{15}=0$, the output elasticity of translog function is equal to the output elasticity of Cobb-Douglas function or estimated parameters. Based on the output elasticity, the cross elasticity of substitution for input factors j and k can be defined as follows[5]:

$$H_{jk}=[\beta_{jk}/(S_j\times S_k)]+1\cdots\cdots(3)$$

From the result of this method, a positive substitution elasticity value implies that the input factors j and k are jointly complementary. In addition, a negative substitution elasticity value indicates a competitive relationship.

Now, we turned to an investigation of environmental efficiency, after the structure of the estimated production technology was considered. According to Reinhard, *et al.*[6,7], the environmental efficiency index could be defined as the ratio of minimum feasibility to an observed input which was environmentally detrimental: $EE=\min\{\text{Ø}: F(X, \text{Ø}Z)\geqslant Y\}\leqslant 1$. Where $F(X, \text{Ø}Z)$ is the frontier function, X is a vector of inputs, Z is a vector of environmentally detrimental inputs and Y is the value of output. To obtain the environmental efficiency index, a new frontier function could be developed by replacing observed Z inputs with ØZ and setting $U_i=0$, representing a function at full technical efficiency. Making newly developed function minus original translog function, if there was only one environmentally detrimental input (we regarded X_5 as the only one environmentally detrimental input), the result could be written as :

$$0.5\beta_{55}[Ln\text{Ø}Z-LnZ]^2+[\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{45}LnX_4+\beta_{55}LnZ](Ln\text{Ø}Z-LnZ)+U_i=0\cdots\cdots(4)$$

Because $LnEE=Ln\text{Ø}=Ln(\text{Ø}Z/Z)=Ln\text{Ø}Z-LnZ$, the above function could be rewritten as:

$$0.5\beta_{55}[LnEE]^2+[\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{45}LnX_4+\beta_{55}LnZ]LnEE+U_i=0\cdots\cdots(5)$$

which could be solved as:

$$LnEE=\{-(\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{45}LnX_4+\beta_{55}LnX_5)+[(\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{45}LnX_4+\beta_{55}LnX_5)^2-2\beta_{55}U_i]^{0.5}\}/\beta_{55}\cdots\cdots(6)$$

If there were two environmentally detrimental inputs (we regarded X_4 and X_5 as two environmentally detrimental inputs), the result should be written as:

$$(0.5\beta_{55}+0.5\beta_{44}+\beta_{45})Ln^2EE+(\beta_4+\beta_{14}LnX_1+\beta_{24}LnX_2+\beta_{34}LnX_3+\beta_{44}LnX_4+\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{55}LnX_5+\beta_{45}LnX_4+\beta_{45}LnX_5)LnEE+U_i=0\cdots\cdots(7)$$

which could be solved as:

$$LnEE=\{-(\beta_4+\beta_{14}LnX_1+\beta_{24}LnX_2+\beta_{34}LnX_3+\beta_{44}LnX_4+\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{55}LnX_5+\beta_{45}LnX_4+\beta_{45}LnX_5)+[(\beta_4+\beta_{14}LnX_1+\beta_{24}LnX_2+\beta_{34}LnX_3+\beta_{44}LnX_4+\beta_5+\beta_{15}LnX_1+\beta_{25}LnX_2+\beta_{35}LnX_3+\beta_{55}LnX_5+\beta_{45}LnX_4+\beta_{45}LnX_5)^2-4(0.5\beta_{55}+0.5\beta_{44}+\beta_{45})U_i]^{0.5}\}/(\beta_{55}+\beta_{44}+2\beta_{45})\cdots\cdots(8)$$

In this function, the "+√ " is applied in the model because if $U_i=0$, only when the "+√ " is used, the LnEE is equal to "0"[1]. Therefore, in this model, the environmental efficiency index was calculated by using:

$$EE=EXP(LnEE)=\text{Ø}=(\text{Ø}Z)/Z$$

Where Ø is the environmental efficiency index.

RESULTS

We used the software package FRONTIER4.1[8] to generate the maximum likelihood estimates of the stochstic translog frontier function. The output-oriented technical efficiency of each farm was assumed to be constant and followed a truncated normal distribution. The stochastic frontier model was specified as time-invariant model. All the estimated parameters are summarized in Table 2. To apply the stochastic production frontier model, a generalized likelihood-ratio statistic should be carried out using the function: $\lambda=-2Ln[L(H_0)/L(H_1)]$. In our model, the generalized likelihood-ratio statistic of null hypothesis "$\gamma=\mu=\delta=0$" was 14.737696 which was significantly higher than the critical value of $\chi^2_{0.05}(7.8147)$ with 3 degrees of freedom.

TABLE 2

Parameter Estimates

Parameter	Coefficient	Standard Error	Parameter	Coefficient	Standard Error
B_0	5.6187	0.9800	B_{13}	0.0489	0.1914
B_1	0.5181	0.7784	B_{14}	0.0384	0.3687
B_2	-0.0704	0.8641	B_{15}	-0.0219	0.0707
B_3	-0.0623	0.8795	B_{23}	0.0114	0.1947
B_4	-0.5982	0.8789	B_{24}	0.0208	0.2876
B_5	0.1472	0.8637	B_{25}	0.0082	0.1913
B_{11}	-0.0803	0.4618	B_{34}	0.0041	0.0607
B_{22}	-0.0039	0.2091	B_{35}	-0.0094	0.1851
B_{33}	-0.0258	0.7986	B_{45}	0.0147	0.0399
B_{44}	0.0686	0.5219	σ^2	0.1653	0.0157
B_{55}	0.0047	0.05095	Log Likelihood	-185.5178	
B_{12}	-0.0038	0.1745			

TABLE 3

Output Elasticity

The Output Elasticity of Translog Function					
	X_1	X_2	X_3	X_4	X_5
Mean	0.322977	0.058838	0.158848	0.091125	0.086485
Median	0.323588	0.063303	0.156990	0.094233	0.086812
Maximum	0.490150	0.136472	0.362867	0.311469	0.153417
Minimum	0.027543	-0.043546	0.063851	-0.161120	0.021770
Std. Dev.	0.058761	0.029421	0.030831	0.087794	0.018312

Based on the estimated parameters in Table 2, we calculated the output elasticities of five input factors. Table 3 depicts the summary statistics of these output elasticities. It was interesting to note that all the mean values of estimated output elasticities were positive, indicating a positive relationship between the output value and input factors. However, the sum of mean output elasticities for five input factors was only 0.718, representing that the vegetable farms in our model exhibited diminishing returns to scale. The estimated elasticities of output with respect to the pesticide input (X_5) were of particular interest in our paper. They had a mean value of 0.086485 with a standard deviation of 0.018, indicating that, making other input factors constant, a 1% reduction of pesticide input might induce a 0.086% decrease in output value. Another important input factor in our paper was the chemical fertilizer use whose average output elasticity was 0.09. It should be indicated here that the minimum values of output elasticities for seed and chemical fertilizer inputs were negative, although the mean values of them were positive.

The cross elasticities of substitution are reported in Table 4. It was interesting to note that in the negative substitution elasticities, there was only one negative average substitution elasticity in Table 4. This negative substitution elasticity for seed and chemical fertilizers indicated a competitive relationship between these two inputs. In other words, a decrease of seed input could be compensated by an increase in chemical fertilizer input. The positive average substitution elasticities in the table implied complementary relationships between the pairs of inputs. These pairs of inputs needed to be increased together to raise total production. For example, if the output level was raised by an increase of labor input, then all the other inputs should also be increased simultaneously. Moreover, if output was increased by increasing seed input, then farmers needed to increase pesticide and labor inputs too.

TABLE 4

Cross Elasticities of Substitution

	Mean	Median	Maximum	Minimum	Std. Dev.
H12	0.223208	0.815405	13.44961	-107.842	6.778302
H13	2.011214	1.978261	5.89271	1.596167	0.26647
H14	2.155028	1.947414	67.29433	-46.9971	6.86015
H15	0.076172	0.193456	0.663835	-20.2243	1.151899
H23	5.210357	2.19961	827.3103	-40.472	43.31401
H24	-4.99836	3.2756	2113.355	-2952.84	209.1313
H25	6.417538	2.487825	1007.986	-159.472	54.90595
H34	1.249697	1.205553	12.05247	-10.6346	1.456749
H35	0.253181	0.292208	0.658575	-1.62931	0.233849
H45	2.581525	2.346377	94.7707	-78.7165	10.39907

The estimated technical efficiencies are summarized in Table 5 and Fig. 1. It should be noted that the technical efficiencies of China's vegetable production were impressively high, ranging from 0.79 to 1 with a mean of 0.96. These high technical efficiency scores indicated that only little output was sacrificed to resource waste. From the frequency distribution of the estimated technical efficiency scores in Table 5, it could be seen that vegetable farms in China were generally operated under an intensive system, although the proportion of intensive farms was quite low in China's total agricultural system. In other words, in China, there was a great potential for increasing vegetable production through improvements in technical efficiency.

TABLE 5

Estimated Technical Efficiencies

Value	Count	Percent	Cumulative Count	Cumulative Percent
[0.75, 0.8]	1	0.27	1	0.27
[0.8, 0.85]	10	2.65	11	2.92
[0.85, 0.9]	56	14.85	67	17.77
[0.9, 0.95]	45	11.94	112	29.71
[0.95, 1]	249	66.05	361	95.76
[1]	16	4.24	377	100.00
Total	377	100.00	377	100.00

Environmental efficiencies for pesticide input were estimated using function (6). The estimated environmental efficiencies are depicted in Table 6. Using the translog frontier model, environmental efficiencies across all vegetable farms were estimated to be 0.69. The most efficient vegetable farm had an environmental efficiency of 1 while the least efficient vegetable farm had an EE of 0.0043. About 18.9% of farms had environmental efficiencies below 0.4. From the frequency distribution of the estimated environmental efficiency scores in Table 6, it is clear that the environmental efficiencies of pesticide use in China's vegetable production were much lower than the technical efficiencies. In addition, environmental efficiencies in Table 6 exhibited a much greater variability than estimated technical efficiency scores. These low environmental efficiency scores indicated that the output value of vegetable farms in China could be maintained using observed values of other inputs, while reducing 31% of the pesticide input. Therefore, in China, there was a great potential for increasing profits of vegetable farms through improvements in environmental efficiency of pesticide input.

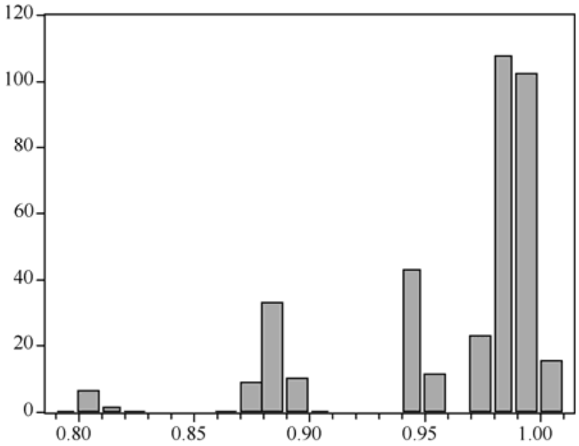

FIG. 1. TE estimates.

TABLE 6

Environmental Efficiencies for Pesticide Input

Value	Count	Percent	Cumulative Count	Cumulative Percent
[0, 0.2)	29	7.71	29	7.71
[0.2, 0.4)	42	11.17	71	18.88
[0.4, 0.6)	45	11.97	116	30.85
[0.6, 0.8)	46	12.23	162	43.09
[0.8, 1)	198	52.66	360	95.74
[1]	16	4.26	376	100.00
Total	376	100.00	376	100.00

Note. One EE could not be solved using our method because “+√ <0 ”.

Environmental efficiencies for both pesticide and chemical fertilizer inputs were estimated using function (8), and the estimated environmental efficiencies of two environmental detrimental inputs are depicted in Table 7. The EEs for two environmental detrimental inputs were higher than the EEs for one environmental detrimental input (pesticide), ranging from 0.21 to 1 with a mean of 0.88. The higher EE scores for two environmental detrimental inputs might result from the higher efficient use of chemical fertilizers in China's vegetable farms. In fact, 75% of farms' EE scores for two environmental detrimental inputs were higher than 0.8. A very interesting issue should be indicated in Tables 5, 6, and 7, namely 16 observed farms were fully efficient at all of technical efficiency, environmental efficiency for one input, and environmental efficiency for two inputs. This issue demonstrated that technical efficiency was both necessary and sufficient for environmental efficiency[1].

TABLE 7

Environmental Efficiencies for Two Inputs

Value	Count	Percent	Cumulative Count	Cumulative Percent
[0.2, 0.3)	1	0.34	1	0.34
[0.3, 0.4)	3	1.03	4	1.37
[0.4, 0.5)	8	2.75	12	4.12
[0.5, 0.6)	5	1.72	17	5.84
[0.6, 0.7)	10	3.44	27	9.28
[0.7, 0.8)	24	8.25	51	17.53
[0.8, 0.9)	36	12.37	87	29.90
[0.9, 1)	185	63.57	272	93.47
[1]	16	5.50	288	98.97
Total	288	100.00	288	100.00

Note. Eighty-six EEs could not be solved and the score of 3 EEs was higher than 1.

Figs. 2 and 3 are the scatter diagrams which independently depict the EEs of one and two environmental detrimental inputs. Both of these figures show that the EEs changed steadily with a very slight variation in the first half observed farms, but they changed suddenly and declined substantially in the last half observed farms. Because the model to estimate technical and environmental efficiencies was specified as time-invariant, the enormous variations in different farms could not be explained by the time change. Such issues might be induced by the difference of different vegetable varieties used in the model, meaning that different vegetable varieties might have different environmental efficiencies.

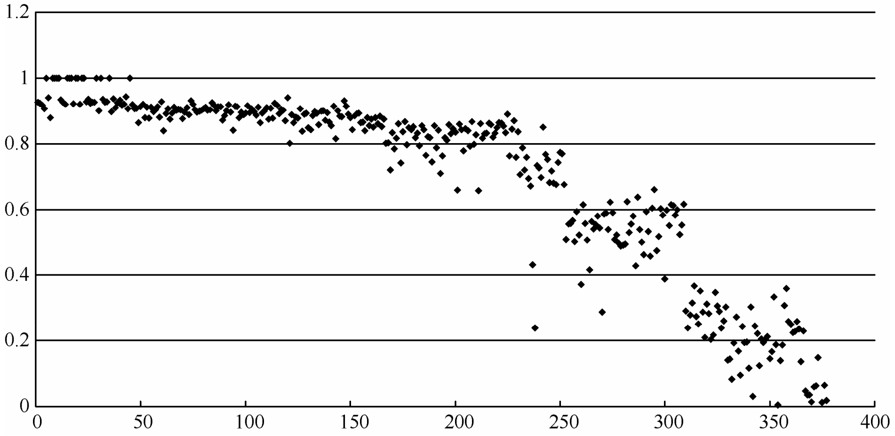

FIG. 2. EE for pesticide.

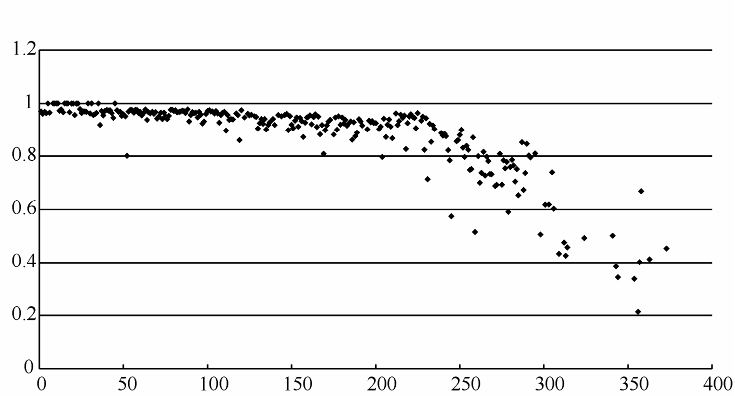

FIG. 3. EE for two variables.

Table 8 reports the mean values of TE and EE scores for eight vegetable varieties used in the model. The TE scores of the first 6 vegetable varieties were similar, but the TE scores of potato and spinach were deviated. As the EE scores for the pesticide input, those of pepper, potato, and spinach were deviated substantially from others. As the EE scores for two inputs, such deviation was obvious in garlic, pepper, potato, and spinach. It should be noted that the spinach's EE score for pesticide input was only 0.049, representing that the environmental efficiency of spinach could be improved greatly by reducing pesticide use. The compatibility of technical efficiency and environmental efficiency was deserved to be considered. Table 8 shows that a relatively high technical efficiency score might be compatible with a relatively low environmental efficiency. For example, the potato's TE score was higher than the spinach's TE score, but the two input EEs of potato were lower than that of spinach.

TABLE 8

TE and EE Scores of Eight Vegetable Varieties

	Mean Value		
	Technical Efficiency	EE for Pesticides	EE for Pesticides and Chemical Fertilizers
Cucumber	0.995	0.948	0.977
Tomato	0.991	0.899	0.956
Cabbage	0.989	0.875	0.935
Celery	0.984	0.818	0.918
Garlic	0.974	0.702	0.848
Pepper	0.947	0.540	0.731
Potato	0.884	0.225	0.426
Spinach	0.806	0.049	0.453

DISCUSSION

Since the present study was based on 377 vegetable farms from 20 provinces in China, the findings in our study may reveal some useful characteristics of vegetable production in this country. From output elasticity estimates, the labor input was found to be an important factor influencing vegetable production in China. The result indicatedthat when the input of labor was increased by 1%, the total vegetable production would be increased by 0.32%. The substitution elasticities estimated in the model can help vegetable farmers deal with adjustments in stochastic variable changes to maintain optimum resource allocation. Information on substitution elasticities can also be useful when the management of input allocations during production planning is to be of benefit from comparative resource advantages. In the model, the mean technical efficiency for the sample vegetable farms was estimated to be about 96%, suggesting that the technical efficiency of China's vegetable production is very high. Such a high mean value of technical efficiency in China's vegetable production may result from the small household farm size and intensive operation. However, the environmental efficiency of vegetable production was significantly lower than the estimated technical efficiency.

Despite remarkable progresses have been achieved in environmental protection and sustainable development, China is still faced with serious problems of environmental pollution and ecological deterioration in vegetable and crop production. Because of the nature of vegetable production which needs a lot of pesticide use, the environmental problems in vegetable production are very severe. In 2001 and 2002, China's vegetable exports to Japan were seriously stifled by Japan's strict inspections and standards with respect to food safety. Thus, in order to sustain the development of China's vegetable industry, it is necessary to increase vegetable productivity and its environmental efficiency. The results of this study are consistent with the real situation of vegetable industry in China. In fact, pesticide residues are the main source of threat to the human health in China's diets.

The estimated mean EE of pesticide input implies that vegetable farmers in China can improve their environmental efficiency greatly by reducing pesticide input. Presently, the average environmental efficiency for pesticide input is 0.697, representing that eliminating 30% of pesticide use would not influence the output level of vegetables. Through such an adjustment in production operation, the cost of inputs can be reduced and the profits of these farmers can be increased. In addition, by this method, the pesticide residues in China's vegetable products would be limited, and China's vegetable products can be exported to Japan's market again. In fact, in 2003, China's exporters successfully exported green vegetables to Japan , which applied only a limited quantity of pesticides and chemical fertilizers. Such a method is very suitable for spinach whose pesticide EE score was only 0.049. In addition, from Table 8, the diversity of vegetable species was found to be a significant contributor to environmental inefficiency in vegetable production. Therefore, the environmental management and pesticide residue monitoring are quite necessary for those vegetables such as spinach and sweet pepper in China. In summary, the comparison of the estimated TE and EE scores under various vegetable species could provide farmers with targets that can be achieved by reallocating input resources and boosting environmental efficiency. As for the relationship between environmental efficiency and intensive farms or extensive farms, it may be different from the relationship between technical efficiency and intensive farms which always has a close positive relationship. The study of Reinhard, *et al.*[1] discovered a positive relationship between environmental efficiency and intensive farms, but such a positive relationship was not pronounced. In our study, such a weak positive relationship was also found, with an estimated parameter of 0.03 using Generalized Method of Moments (GMM).

CONCLUSIONS

In this paper, a stochastic translog production frontier was estimated in order to assess the level of technical efficiency for a set of vegetable farms in China. Based on the estimated frontier and technical inefficiency level, we used the method developed by Reinhard, *et al.*[1] to estimate the environmental efficiency. In this paper, two kinds of environmental efficiency index were estimated. One was based on the pesticide input and the other was based on environmental efficiency with two environmentally detrimental variables. The production frontier involved five input variables, including seed, labor, chemical fertilizer, organic fertilizer, and pesticide inputs. All estimated output elasticities in the stochastic translog production frontier were estimated to be positive and the results indicated that these inputs made a positive contribution to vegetable production in China. Furthermore, vegetable farming in China exhibited diminishing returns to scale, i.e., a 1% increase in all input factors would result in less than 1% increase in output. This study also estimated cross substitution elasticities to identify which inputs farmers could switch and to what degree. The mean technical efficiency for the sample farms, estimated by the stochastic production frontier, was quite high, but the estimated environmental efficiencies were low, especially for the pesticide input,which represents the fact that current pesticide use on China's vegetables is excessive and there is a great potential for reducing pesticide use in China's vegetable production. The results from the environmental efficiency estimate indicate that the differences in various vegetable varieties contribute significantly to the level of and variations in environmental efficiency of vegetable production in China. It is also discovered that the intensive culture system is more efficient than the extensive system. Moreover, Table 8 shows that although there may be a positive relationship between technical efficiency and environmental efficiency, some exception is existent. If the sample size can be increased to be large enough, production frontiers can be estimated separately for various vegetable species.

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