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MEASUREMENT AND ANALYSIS OF AGRICULTURAL WASTE RECYCLING EFFICIENCY

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Abstract

Research on the efficiency of agricultural waste recycling by farmers is helpful to help us understand the status of agricultural waste recycling based on micro perspective From this perspective, this paper uses a three-stage Data Envelopment Analysis model to measure the agricultural waste recycling efficiency of peasant households. Through research, the concludes that the three-stage Data Envelopment Analysis model seems more scientific and rational to measure the performance of farmers' behaviors in this regard; there is a certain efficiency difference between sample farmers before and after adjustment of resource inputs, to a certain extent, which shows that the environmental variables and random factors have a significant impact on farmers' production behaviors; the farmers' waste recycling performance is also low, and the efficiency difference between sample farmers is marked, all of these may be attributed to a low production scale efficiency of peasant households.

Key words: agricultural waste recycling, efficiency, Three-Stage DEA (TSDEA) model

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1. Introduction

The construction and continuous improvement of the modern agricultural industry technology system provides a good information exchange platform and mechanism for the matrix recycling of agricultural waste. In order to further promote the conversion and utilization of agricultural waste and the efficient and sustainable development, agricultural waste needs to be improved. The transformation utilizes in-depth investigations and understanding analysis (Ahmed and Hoque, 2018; Al-Ghumaiz, 2019; De Silva, 2019; Jian and Wang, 2018; Straka et al., 2018; Tomkins et al., 2019). This paper takes farmers as the research object, constructs an index system, and discusses the behavioral performance of farmers in the process of matrix waste recycling of agricultural waste, which verifies the reliability and scientificity of the three-stage Data Envelopment Analysis (TSDEA) method adopted by the author. According to relevant research conclusions, countermeasures and suggestions are proposed to improve the degree of industrial specialization and strengthen the construction of rural infrastructure, so as to achieve the moderate scale and industrialization of agricultural waste matrix recycling. To make up for the gaps of the traditional Data Envelopment Analysis model, a more mature three-stage Data Envelopment Analysis (TSDEA) model (Fried et al., 2002) is adopted to integrate the traditional DEA with the SFA methods in an attempt to achieve good quantitative properties (Vaisi et al., 2018). It includes the following three phases:

1. the traditional DEA model is built based on input-output data of the study subject to measure the technical efficiency of its behaviours;
2. the SFA regression analysis is introduced to set up a regression equation with the input and output slacks as dependent variable and the external environment factor as the independent variable, and the initial inputs and outputs are further adjusted;
3. the adjusted inputs and outputs are substituted into the traditional DEA model to determine the

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technical efficiency of the decision unit again. It is found that the technical efficiencies that are subjected to the external environment divestiture and statistical noise etc., are more accurate and reliable.

2. Material and methods

2.1. Data sources

Based on the industrial technology system in modern agriculture, a questionnaire survey is conducted among 616 peasant households randomly chosen in Heilongjiang, China, as the samples, on the agricultural waste treatment. China's Heilongjiang, as a large agricultural production province, has a strong representativeness in the recycling of agricultural wastes. In view of this fact, the paper takes the questionnaires collected from 220 peasant households in Heilongjiang, China, as the samples to analyze the recycling efficiency of agricultural wastes.

2.2. Input-output indicators

In order to truly reflect the recycling performance of agricultural wastes, in the process of indicator selection, it should make certain that the selected input-output indicators are highly correlated to agricultural waste utilization (Chang et al., 2014; Dutreuil et al., 2014). In addition to this, one of the conditions for developing the TSDEA model is the homogeneity of the decision units. In this paper, the farmers involved in the recycling of agricultural wastes are therefore chosen to conduct surveys since all of them face one external environment on the whole (Havukainen et al., 2016).

After the decision units of the TSDEA model have reached the homogeneity, the selection and assignment of the input and output indicators for sample farmers should also satisfy the following conditions: First, the sample farmers all use consistent input and output indicators which take positive values; Second, the selected indicators are important input elements for agricultural wastes; third, the indicator units may be inconsistent. Sample data will be collated on the premise that the agricultural waste utilization process of farmers has been subdivided. Input-output indicators for the farmers' recycling behavior performance of agricultural wastes will then be determined (Table 1).

This paper chooses the farmer's operation income of recycling agricultural wastes as the output indicator. There are several input indicators: (1) human capital investment (technical training), i.e. the frequency of the farmers’ involvement in technical guidance and training in the process of recycling agricultural wastes; (2) Direct input of production means, the management for agricultural wastes requires heavy inputs of production materials, such as crop straw, agricultural machinery, film, etc.; (3) labour force, the recycling of agricultural wastes requires plenty of labour resources, labour inputs in man-day, based on 8 h a day.

2.3. Setting of environment variables

External environment variables have important impacts on the recycling performance of agricultural wastes, which cannot be effectively improved and controlled by the sample farmers themselves (Dai et al., 2015; Li et al., 2018). The SFA regression and decomposition will eliminate external impact of environmental variables on the performance of farmers' recycling behaviors (Kirchmann et al., 2017; Mahmoud et al., 2017). In this paper, 6 environmental variables are chosen and set up as applicable to the practical recycling conditions for agricultural wastes, as shown in Table 2:

(1) age of householder, it reflects the impacts from the age level and health degree, etc., of agricultural production policymakers on the agricultural waste disposal performance;

(2) education background of householder, the education level of the sample farmers directly determines their ability to learn and accept technical skills, so that it will play a definite effect on the recycling performance of agricultural wastes;

(3) whether the government has carried out technical training on agricultural waste recycling. This variable reflects the impact of policy factors on the recycling performance of agricultural wastes to a certain extent since the government plays a leading role in the recycling of agricultural wastes.

(4) operation income of agricultural waste recycling behaviors as a percentage of the total income of peasant households.

Table 1. Indicators for measuring recycling performance of agricultural wasters and statistical properties

Indicators	*Indicator description*	*Dimension*	*Mean*	*Standard deviation*	*Min*
Inputs	Human capital investment: training	Frequency	3.61	1.92	1
	Direct production data input	RMB	39210.32	262.21	450
	Labour force	Man-day	781.53	56.52	5.2
Outputs	Recycling operation income	RMB	35623.11	183.72	4500
Indicators	Indicator description	Dimension	Mean	Standard deviation	Max
Inputs	Human capital investment: training	Frequency	3.61	1.92	6
	Direct production data input	RMB	39210.32	262.21	500000
	Labour force	Man-day	781.53	56.52	35000
Outputs	Recycling operation income	RMB	35623.11	183.72	45000

Table 2. Statistical properties of environment variables

Statistical variables	***Assignment description***	***Mean***	***Standard deviation***	***Min***	***Max***
Age of householder	***Age***	***44.21***	***5.31***	***24***	***64***
Education level of householder	1=primary school and below, 2=junior high school, 3=high school or technical secondary school, 4=college and above	2.11	1.12	1	4
Whether government hosts relevant training	1=Yes, 2=No	1.31	0.58	1	2
Operation income as a percentage of total family income	%	65.24	37.21	12	100
Whether they participate in specialized ECOs	1=Yes, 2=No	1.38	0.59	1	2
Circumjacent traffic conditions	1=country dirt road, 2=village to village road, 3=county road, 4=provincial highway, 5=national road and above	2.42	1.62	1	5

It reflects the impact of the sideline activities of farmers on the performance of agricultural waste recycling behaviors; (5) whether they participate in specialized economic cooperation organizations since such organizations will play an important role in directing farmers' behaviors and promoting the recycling of agricultural wastes, so that it reflects the impact on the performance of agricultural waste recycling behaviors; (6) circumjacent traffic conditions, the grades of surrounding roads reflect the traffic conditions around policymakers responsible for disposal of agricultural wastes. How well is the surrounding traffic condition directly affects the circulation of agricultural wastes and indirectly holds up their recycling behaviors. This variable is used to reflect what's the impact of local infrastructure conditions on the agricultural waste recycling performance of peasant households.

As shown in Tables 1- 2, there is a certain difference in the input and output indicators between the sample farmers in the recycling process of agricultural wastes, which may be rooted in the difference in the farming scale and production efficiency of the farmers.

2.4. Methods

Traditional DEA. Data envelopment analysis is a method for performance evaluation of decision units with the same type. Here the same type means that this type of decision unit has the same nature of inputs and outputs. A decision unit is an operating entity that can convert certain inputs into corresponding outputs.

There are two types of the traditional DEA models, i.e. CRS and VRS. The CRS model applies to all decision making units to achieve optimal scale in the recycling process of agricultural wastes, while the VRS model can measure the technical efficiency without the interference of scale efficiency. In order to make sure the results are accurate and approach to the truth, this study adopts the Variable Return to Scale (VRS) model to measure the behavioural efficiency of the sample subjects. This process can be achieved with MATLAB software (Eq. 1).

$$\begin{cases} \underset{\vartheta,\lambda}{Min}\ \vartheta^k \\ s.t. \sum_{k=1}^{220} \lambda_k x_{n,k} \le \vartheta^k x_{n,k}\ (n=1,2,3) \\ y_{m,k} \le \sum_{k=1}^{220} \lambda_k y_{m,k}\ (m=1) \\ \lambda_k \ge 0 (k=1,2,\cdots,220) \\ \sum_{k=1}^{220} \lambda_k = 1 \end{cases} \tag{1}$$

where: involving 220 decision-making units, each sample subject has n inputs and m outputs, for the kth decision making unit, use the column vectors $x_{n,k}$ and $y_{m,k}$ to represent the inputs and outputs of the agricultural waste recycling subject. λ_k represents the weighting coefficient of the nth input and the mth output; ϑ^k represents the efficiency value of the kth farmer, the value range is (0,1), the closer to the representative the higher the efficiency, the unit of $\vartheta^k = 1$ is the most efficient decision. In addition, $x \ge 0$, $y \ge 0$, and $n = 3$, $m = 1$.

SFA Model. In order to further explore why the overall efficiency of the sample subject measured by the traditional DEA model loses, whether it derives from management efficiency loss, or external environment or statistical noise, the SFA regression analysis is introduced to decompose those factors that cause the original input or output slacks, such as internal management failure (Alves-Filho, 2018; Fried et al., 2002), the external environment and statistical noise, to find out what's the effect of internal management loss and statistical noise on the slack values, and judge what are the directions and extents of the impact factors on the slack variables.

It is determined that the dependent variable in the SFA regression, that is, the input slack (S_{nk}) in (Eq. 1) DEA analysis, as shown in (Eq. 2):

$$S_{nk} = x_{nk} - \sum_{k=1}^{k} \lambda_{nk} \ge 0 \tag{2}$$

where: S_{nk} is the input slack n of the decision subject k in the traditional DEA analysis; x_{nk} is the actual inputs of the element n in the decision unit k. In addition, λx_{nk}

corresponds to the optimal mapping of x_{nk} on the corresponding output vector y_k.

Build an SFA regression model of slack and environment variables, as shown in (Eq. 3):

$$S_{nk} = f_n(z_k; \beta n) + v_{nk} + u_{nk} \quad n=1, 2, 3; k=1, 2,\ldots, 220 \quad (3)$$

In (Eq. 3), $f^n(z_k; \beta^n)$ is the slack frontier function, which can reflect the effect of environment variables on the input slacks, and may also be expressed as $f^n(z_k; \beta^n)= z_k\beta^n$, where, $z_k=[z_{1k}, z_{2k}, \ldots, z_{pk}]$, k=1, 2, …, 220 is the observable value of p environment variables, while the vector β^n is the coefficient to be evaluated; $v_{nk}+u_{nk}$ is the error term, where, v_{nk} represents the statistical noise; u_{nk} means the management is invalid; v_{nk} and u_{nk} are independent of and irrelevant to each other, and it is assumed they conform to a normal distribution, i.e. $v_{nk}\sim N(0,\sigma^2_{vn})$, $u_{nk}\sim N(\mu^n,\sigma^2_{un})$.

Next, assume $\gamma=\sigma^2_{uk}/(\sigma^2_{uk}+\sigma^2_{vk})$, when γ tends to 1, the management failure is considered to be the dominant factor; when γ tends to 0, the random statistical noise is the dominant factor. In addition, with regard to the acquisition of z_k, the maximum likelihood estimation is used to obtain the regression coefficient, while (μ^n, σ^2_{un}, σ^2_{vn}) is also required to construct a regression model and estimate its parameters.

Variable adjustment. The way that sample subject v_{nk} is captured is to separate the residual term from management failure, which is also the primary task before the input adjustment. The error term in (Eq. 3) is separated mainly to estimate the results $\hat{E}[u_{nk}/(v_{nk}+u_{nk})]$, $\hat{\beta}^n, \hat{u}^n, \hat{\sigma}^2_{vk}, \hat{\sigma}^2_{uk}$ and other parameters as given the management failure. The derived statistical noise estimation is shown in (Eq. 4):

$$\hat{E}[u_{nk}/(v_{nk}+u_{nk})] = s_{nk} - z_k\hat{\beta}^n - \hat{E}[u_{nk}/(v_{nk}+u_{nk})] \quad (4)$$

In order to make sure that each decision unit faces one external environment and tries the same operation luck, it is necessary to adjust the inputs in those decision making units that are in a more favourable environment or have good luck. Based on the SFA regression results, the adjusted input variable is defined as (Eq. 5):

$$x^A_{nk} = x_{nk} + [max_k\{z_k\hat{\beta}^n\} - z_k\hat{\beta}^n] + [max\{\hat{v}_{nk}\}k - \hat{v}_{nk}], \; n=1, 2, 3; k=1, 2, \ldots, 220 \quad (5)$$

where: x^A_{nk} and x_{nk} represent the adjusted input variable and the observed input variable, respectively; $\hat{\beta}^n, \hat{v}_{nk}$ are explained as above; $max_k\{z_k\hat{\beta}^n\} - z_k\hat{\beta}^n$ means that all the samples have a consistent worst environment; $max\{\hat{v}_{nk}\}k - \hat{v}_{nk}$ represents that all the samples try the same luck, and al run worst (random error).

DEA Model. In the process of disposing agricultural wastes, the external environments that sample farmers face differ a lot, resulting in differences in the performance of farmers' recycling behaviours for agricultural wastes (De Vries et al., 2012; Wang et al., 2018;). It is therefore required to adjust the input variables in Eq. (1) based on the external environment and random disturbance factors, so that the same external environment may be obtained for sample farmers to measure the technical efficiency level of farmers' recycling of agricultural wastes more accurately. This process can be achieved with Matlab software. The adjustment is shown in Eq. (6):

$$x^A_{nk} = x_{nk} + [max_k\{z_k\hat{\beta}^n\} - z_k\hat{\beta}^n] + [max\{\hat{v}_{nk}\} - \hat{v}_{nk}] \quad (6)$$

The adjusted input x^A_{nk} replaces the original input x_{nk}, and the value measured by DEA model in Eq. (1) is substituted into the formula again. The impacts from the operation environment and random factors are erased up. The re-substitution of measurements of DEA model in (Eq. 1) will more objectively reflect the performance of sample farmers.

3. Results and discussion

3.1. Phase 1: application of traditional DEA

In the Phase 1, based on the input-oriented VRS model Eq. (1), the MATLAB software is used to measure the technical efficiency of sample farmers, as shown in Table 3.

Regardless of management efficiency loss, environmental variables and random disturbance, the average recycling efficiency of agricultural wastes is 0.45, the average technical efficiency is 0.65, and the average scale efficiency is 0.70. It means that, at the existing input-output scale and technology level, if the technical efficiency loss can be erased up, there is still 50% room for improvement in the technical efficiency of the agricultural waste recycling.

Table 3. Average efficiency in Phase 1

Efficiency types	*Overall efficiency*	*Pure technical efficiency*	*Scale efficiency*
Mean	0.45	0.65	0.70

3.2. Phase 2: SFA regression and decomposition

SFA regression analysis. Based on the traditional DEA model in the Phase 1, the original input slack is regarded as the dependent variable, and the environmental factors that affect the recycling performance of agricultural wastes as independent variables.

The empirical results show that the value γ in the regression equations of each input slack falls within 0.6 ~ 1 and is at 1% significance level. It is observed that there is a difference in management efficiency of the agricultural waste recycling behaviours between the sample farmers, so that the SFA regression model is reasonable (Table 4).

Table 4. SFA estimation results

Variables	***Human capital (training)***
	Input slack
Age of householder	4.2663 (1.3962)
Education level of householder	-36.9658 (0.8296)
Whether government hosts relevant training	-28.6321 (0.3506)
Operation income as a percentage of total family income	36.2588 (1.6523)
Whether they participate in relevant specialized ECOs	-99.6238*** (38.2569)
Circumjacent traffic conditions	25.1730 (1.0122)
σ^2	286321.32*** (4.9826)
γ	0.6181*** (15.6236)
log likelihood function	-2112.3202
Variables	Production materials
	Input slack
Age of householder	0.1782 (0.9812)
Education level of householder	-1.5216 (1.1205)
Whether government hosts relevant training	-0.9821 (1.6987)
Operation income as a percentage of total family income	8.9802*** (4.2569)
Whether they participate in relevant specialized ECOs	-5.6879*** (4.0254)
Circumjacent traffic conditions	0.8962 (0.8932)
σ2	5825.13*** (3.2531)
γ	0.8972*** (3.0021)
log likelihood function	3025.1287
Variables	Labor force
	Input slack
Age of householder	0.1023 (1.2583)
Education level of householder	-7.2018*** (3.6892)
Whether government hosts relevant training	-29.6218*** (3.2658)
Operation income as a percentage of total family income	30.6578*** (6.5821)
Whether they participate in relevant specialized ECOs	-6.8792***(6.3258)
Circumjacent traffic conditions	-8.3621*** (4.2568)
σ2	32988.16*** (2.8920)
γ	0.8952*** (4.1021)
log likelihood function	-3215.6326

*Note: *** means it is significant at 1%, and there is standard error in parentheses*

SFA regression is done by the environment variable on the slack variable of input elements. That the regression coefficient is positive (negative) means that as the assignment of environment variables multiplies, it is certain the corresponding input slack variable will increase (decrease), that is, the inputs more tend to be wasted or the outputs to be inefficient (efficient). In addition, when the environmental variables are not significant statistically, the environmental variables have only a directional effect on the input slack variables. The SFA regression results show:

Age of the householder. As the householder ages, the three types of input slack variables will be caused to increase, but none of them can undergo the significance test. It is only the directional effect.

Education background of sample farmers. The improvement of the education level of the sample farmers can restrain the waste of technical training, direct production materials and labour input, but the slack of technical input and labour input is not statistically significant, and only has a directional effect.

The education level of the sample subject is closely related to the acceptance of advanced technologies of agricultural waste matrixing, which will inhibit investment and improve management performance.

Whether the government often carry out technical training on the recycling of agricultural wastes. SFA regression results show that the government makes efforts to intensify the technical training for farmers, which can effectively restrain the slack in input variables, especially in the labour force.

Operation income as a percentage of total income of peasant household. If the agricultural waste recycling operation income as a percentage of total income of peasant household is raised, this will lead to waste of inputs, especially in terms of production materials and labour force. It will have a statistically significance at 1%.

Whether they participate in relevant specialized ECOs? SFA regression results show that active participation in the ECO can effectively suppress the slacks of input variables and improve the utilization efficiency of resources. Specialized ECOs can join farmers to the markets, and imparts farmers about relevant technologies, thereby reducing the technical inefficiency behaviours of sample farmers.

Circumjacent traffic conditions. The improvement of traffic conditions around the sample area can effectively suppress the slack in labour force inputs and is statistically significant at the level of 1%.

3.3. Phase 3: DEA analysis

As shown in Table 5, after eliminating the impact from the environmental variables and random errors, the average efficiency of agricultural waste recycling in the phase 3 sample farmers is 0.39, and there is still 61% room for improvement; the pure technical efficiency is averaged as 0.96 and behaves well; the average scale efficiency is 0.43, so that it is the dominant factor that leads to the low recycling performance of agricultural wastes. The non-parametric method (Wilcoxon Matched-Pairs Signed-Ranks Test (Wilcoxon)) and the Sign Test are used to test whether the agricultural waste recycling performance value obtained in the phase 3 after the environment factor is independent of the others and the technical efficiency measured in Phase 1 have a significant difference.

Table 5. Average efficiency in phase 3

Efficiency types	***Overall technical efficiency***	***Pure technical efficiency***	***Scale efficiency***
	0.39	0.96	0.43

Test results show that the two sides of the Wilcoxon test and the Sign Test P = 0.0000, which means that there is a significant difference in the technical efficiencies measured in the two phases (see Table 6).

Table 6. Nonparametric test of two relevant technical efficiency values

Test method	***Wilcoxon***	***Sign Test***
Value Z	-6.2136	-5.9872
Two-tailed P Value	0.0000	0.0000

As shown in Table 6, the efficiencies of the phase 3 sample farmers are listed, compared with that of phase 1 (Table 3): After removing the effects played by the environmental variables and random errors, the mean value of overall recycling efficiencies of agricultural wastes in the phase 3 all somewhat decrease, and down to 0.4089 from 0.4516; while the average of pure technical efficiencies significantly increases, and going up to 0.96 from 0.65; the average scale efficiency decreases significantly from 0.70 to 0.43. The DEA analysis results after adjusting the input variables show that the average recycling efficiency of agricultural wastes in the phase 3 is lower than that measured in the phase 1, and the difference in performance and distribution among sample farmers is much wider, leading to such a fact that it attributes the low recycling efficiency of peasant households on agricultural wastes to a low scale efficiency. Therefore, they should appropriately expand the production scale of the decision making units for agricultural waste recycling as an effective way to improve the management performance of farmers.

Based on farmer behaviour research, further research and analysis are carried out using the TSDEA model and its derived DEA-Tobit two-step model, after removing environmental variables and random error effects, this paper analyses the measurement of the efficiency of agricultural waste recycling technology and the main reasons for the low performance of farmers' behaviour.

4. Conclusions

Given the above, when the TSDEA model is applied to measure the performance of agricultural waste recycling behaviors of farmers, there is a certain difference in the technical efficiency between sample farmers before and after adjustment of inputs. It means that the environmental variables and random factors have a significant impact on production behaviors of farmers to a certain extent, and that the TSDEA model is more scientific and reasonable for the measurement of farmer behaviors. Besides, the reasons why the farmers' waste recycling performance is low and the efficiency difference between sample farmers is marked are that there is a low production scale efficiency of peasant households.

Based on the above conclusions, the following policy implications can be obtained. First, increase the degree of industrial specialization. The agricultural waste matrix industry plays an important role in prospering rural economic development, increasing farmers' income, and ensuring agricultural ecological security. Gradually increasing the degree of specialization, realizing the scale and industrialization of the matrix industry are conducive in improving agricultural waste as well as for recycling industry linkage performance. Second, it is important to guide and encourage farmers to participate in professional technical and economic cooperation organizations, which have an irreplaceable role in guiding farmers to regulate production, ensure market circulation, and achieve effective docking between farmers and markets. All these can be very effective in promoting innovation in farmers' organizations, and effectively improving agricultural waste. The scale efficiency of the industrial recycling industry will further improve the overall management performance and strengthen rural infrastructure construction.

Generally speaking, the improvement of traffic conditions can facilitate farmers' contact with the outside world, improve their own knowledge and management skills, thereby reducing the technical inefficiency of farmers, strengthening rural infrastructure construction and providing the infrastructure foundation for industrial development. In addition, the improvement of farmers' educational level is conducive to further improving the pure technical efficiency of industrial linkage. Therefore, it is also urgent and necessary to reinforce the human capital investment of farmers.

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