Pol. J. Environ. Stud. Vol. 33, No. 5 (2024), 5127-5140
DOI: *10.15244/pjoes/182907* ONLINE PUBLICATION DATE: 2024-04-11

Original Research

Agricultural Productive Services and Ecological Efficiency of Cultivated Land Use: Evidence from Hunan Province, China

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Received: 15 April 2023
Accepted: 20 January 2024

Abstract

Agricultural productive services are fundamental in transforming the paradigm of agricultural development and exert a significant impact on farmers' behavior in managing their arable land. This paper employs the slack-based measure of the super-efficiency model, known as the Super-SBM model, incorporating unexpected output to gauge the eco-efficiency of cultivated land use (ECLU). Utilizing panel data from Hunan Province spanning the years 2007 to 2020, this study unveils the following key findings: (1) Across various quantile levels, agricultural productive services exhibit a substantial capacity to enhance ECLU, with coefficients ranging from 0.070 to 0.156. (2) The impact of agricultural productive services on ECLU is constrained by both farmers' income levels and the scale of cultivated land, revealing a dual threshold effect. As income levels rise, the corresponding coefficient increases progressively, from 0.0771 to 0.1147, and ultimately to 0.1571. Similarly, with the expansion of cultivated land, the coefficient increases from 0.1152 to 0.1443, and ultimately peaks at 0.1694. (3) The enhancement of ECLU through agricultural productive services is achieved by reducing the input of environmental factors and mitigating undesirable outputs. (4) Agricultural productive services indirectly facilitate labor transfer, accounting for 10.8% of the overall effect. Consequently, it is imperative to continually enhance the agricultural socialized service system, bolster financial support, and implement policies that foster the development of agricultural productive services to realize sustainable cultivated land utilization.

Keywords: agricultural productive services; eco-Efficiency of cultivated land use; threshold effect; intermediary effect

Introduction

Cultivated land, as the scarcest resource in China, stands as the fundamental production factor for agriculture. Its effective utilization holds paramount importance for sustainable agricultural development and food security [1, 2]. The global challenge of reconciling population growth with limited cultivated land resources [3-5] is particularly acute in China [6]. When harnessing cultivated land for production, the ecological pollution of China's cultivated land ecosystem poses a pressing concern, primarily due to carbon emissions resulting from the use

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of chemical fertilizers, pesticides, and residual films [7]. This not only escalates the cost of agricultural production but also culminates in soil hardening, detrimentally affecting the quality of cultivated land [8, 9].

Furthermore, with the rapid pace of urbanization and industrialization in China, the tension between population expansion and the scarcity of cultivated land resources has grown more pronounced [10]. Regrettably, effective mitigation of cultivated land degradation in the short term remains elusive [11, 12]. Adding to the complexity is the fact that China's cultivated land use efficiency remains suboptimal, primarily due to the extensive agricultural production methods adopted by small-scale farmers [13-15], further exacerbated by regional disparities [16]. Hence, it becomes evident that the pursuit of a strategy to enhance the eco-efficiency of cultivated land use (abbreviated as ECLU) is not merely advisable but imperative.

The scale of service operations offers fresh perspectives for enhancing ECLU. Among these, agricultural productive services stand out as a crucial means to achieve environmentally friendly agricultural production [17]. They not only drive agricultural productivity but also facilitate the modernization of agriculture [18]. By enabling scale operations, agricultural productive services can reduce the costs of agricultural production while preserving the rights of land management [19]. Additionally, the direct impact of nonagricultural labor migration on farmers' access to agricultural productive services should not be underestimated [20]. However, it's worth noting that there are significant variations in how labor migration affects ECLU [21-23].

In the context of green agricultural development and a substantial outflow of rural labor to nonagricultural sectors, the role of agricultural productive services in shaping ECLU deserves profound examination. Although existing literature has explored the correlation between agricultural productive services and climate-smart agricultural production behavior [24], it primarily centers on enhancing green agricultural production through the improvement of technical efficiency [25] and optimization of resource allocation [17]. Notably, four critical gaps are discernible: (1) Existing research predominantly concentrates on agricultural green development but lacks an analysis of ECLU from the perspective of agricultural productive services; (2) The underlying impact mechanisms remain insufficiently elucidated; (3) Prevailing literature often assumes a simplistic linear model and neglects the possibility of nonlinear effects and threshold characteristics; (4) Most relevant studies rely on micro-level surveys of individual farmers or provincial-level panel data. Our study, however, is focused on county-level panel data. Compared to micro-level individual data and provincial panel data, county-level data provides a more comprehensive understanding of ECLU's actual status, rendering our research more explanatory.

Based on the measurement of agricultural carbon emissions and nonpoint source pollution, this paper explores the impact mechanism, threshold characteristics, and intermediary effects of labor transfer of agricultural productive services on ECLU based on county-level data in Hunan Province. This study is a useful supplement to previous research. Our study aims to provide valuable insights and reference points for achieving sustainable utilization of cultivated land resources, addressing food crises, and mitigating global warming.

Mechanism Analysis

Previous research on the ECLU [26, 27] has focused on various factors influencing it. Scholars examined urbanization [28], agricultural production conditions [29], income level [30], agricultural planting structure [31], and rural labor migration [32]. The ECLU encompasses economic, ecological, and social benefits [33] and is influenced by agricultural input, output, carbon emissions, and nonpoint

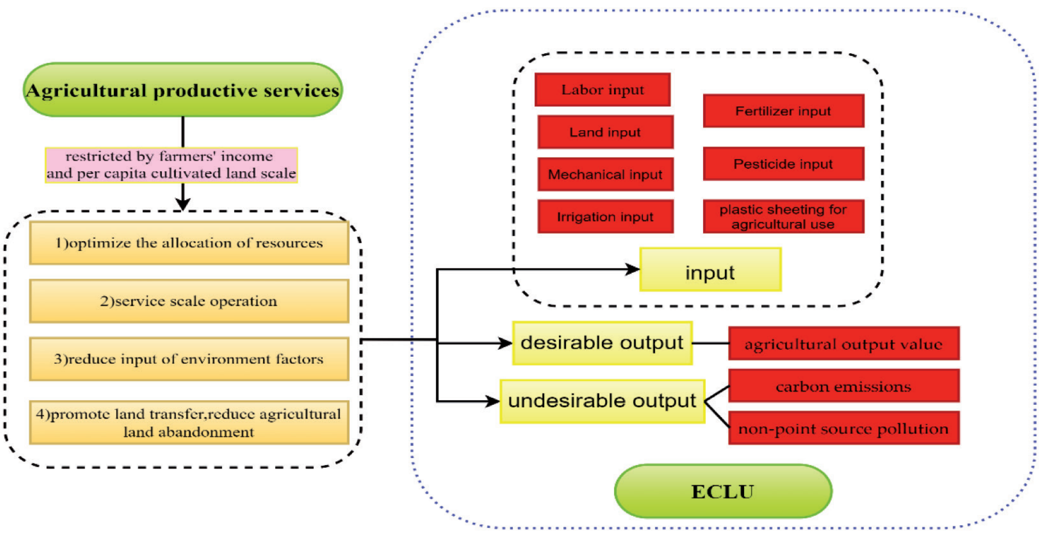

Fig. 1. Influencing mechanism.

source pollution [34], all of which are impacted by agricultural productive services. Also known as agricultural production outsourcing, these services have experienced rapid growth in recent years [35] and have become a key driver of agricultural modernization [36]. Amidst the massive transfer of rural labor to non-agricultural sectors, agricultural productive services have made significant contributions to China's food security, with 11 consecutive years of positive growth in grain production [37, 38].

Agricultural productive services impact the ECLU in four main ways (Figure 1). Firstly, these services introduce modern production factors such as capital, technology, and management to enhance agricultural technological progress [39]. This progress leads to increased specialization, division of labor, and cooperation in agricultural production, ultimately improving farmland productivity [40]. Moreover, agricultural productive services enable land-scale management through mechanisms like land circulation, enhancing the utilization efficiency of cultivated land through economies of scale [41-43]. It is noteworthy that some scholars have noted that agricultural productive services can increase grain output and improve the efficiency of farmland utilization with certain inputs [44]. For example, agricultural machinery services increase rice yield by 48.0 kg, 23.7 kg, and 7.9 kg during farming, transplanting, and harvesting, respectively [45]. These services also contribute to cost savings and improved efficiency [46], resulting in stable production, increased income, and reduced costs in agricultural production [47].

Secondly, agricultural productive services significantly reduce pesticide usage and application costs for farmers while maintaining output levels [48]. Through professional management and intensive production, these services can reduce the input of pesticides, fertilizers, and other environmental factors, thereby improving the ECLU while achieving the desired output. Furthermore, agricultural machinery services, a crucial component of productive services, have a positive impact on farmers' adoption of green production technologies [49, 50], leading to reduced agricultural carbon emissions and unexpected outputs.

Further analysis indicates that farmers' income and cultivated land scale influence their decisions to purchase agricultural productive services [51]. Based on this, this paper suggests that the impact of these services on the ECLU may be constrained by farmers' income and cultivated land scale, highlighting the need for further exploration of threshold characteristics.

Materials and Methods

Measurement of Ecological Efficiency of Cultivated Land Use

Measurement Method

Compared to traditional DEA models, the slack-based measure of the super-efficiency model (Super-SBM model) with unexpected output not only avoids deviations caused by radial and angular measurements, but also considers the impact of non-expected output factors in the production process, which can better reflect the essence of efficiency evaluation. Therefore, this paper uses the SBM model with unexpected outputs to measure ECLU. The main reason is that the input of chemical fertilizers and pesticides into the agricultural production process will destroy the ecological environment. Consequently, when measuring agricultural output, we should not only pay attention to agricultural output value, but also pay attention to the impact of agricultural production on the ecological environment. The basic principle of super-efficiency SBM with unexpected output is as follows: assume that there are n decision-making units (DMUs) in agricultural production, and each decision-making unit is composed of an input vector, an expected output, and an unexpected output. Three sets of vectors are defined as $x \in R^m$, $y^e \in R^a$, $y^n \in R^b$ where m, a, and b represent m input elements, a expected output and b unexpected output, respectively. Define the matrix X、Y^e、Y^n expressed as $X = [x_1, \dots\dots, x_n] \in R^{m\times n}$, $Y^e = [y_1^e, \dots\dots, y_n^e] \in R^{a\times n}$, $Y^n = [y_1^n, \dots\dots, y_n^n] \in R^{b\times n}$, and X、$Y^e$、$Y^n$ are greater than 0. Under constant returns to scale (CRS), the production possibility set is defined as $P = \{(x, y^e, y^n | x \geq X\lambda, y^e \leq Y^e\lambda, y^n \geq Y^n\lambda, \lambda \geq 0)\}$, then, the super-efficiency SBM model is:

$$\begin{cases} \rho^* = min\dfrac{1-\frac{1}{m}\sum_{i=1}^{n}\frac{D_i^-}{x_{i0}}}{1+\frac{1}{a+b}\left(\sum_{r=1}^{a}\frac{D_r^e}{y_{r0}^e}+\sum_{h=1}^{b}\frac{D_h^n}{y_{r0}^n}\right)} \\ s.t.\quad x_0 = X\lambda + D^-, y_0^e = Y^e\lambda - D^e, y_0^n = Y^n\lambda + D^n \\ D^- \geq 0, D^e \geq 0, D^n \geq 0, \lambda \geq 0 \end{cases} \tag{1}$$

In Formula 1, D^-, D^e, and D^n are relaxation variables, which represent input redundancy, expected output insufficiency, and unexpected output redundancy, respectively; ρ^* indicates the eco-efficiency of the decision-making unit.

Selection of Input–output Indicators

The article is based on the connotation and combines the requirements and reality of the development of ECLU [12, 31], 7 types of input indicators, 1 type of expected output, and 2 types of unexpected output are selected to construct the evaluation index system of ECLU, in which the input indicators are land input, labor input, fertilizer input, pesticide input, plastic sheeting for agricultural use input, agricultural machinery power input, and irrigation input (Table 1). The expected output is represented by the total agricultural output value, and the unexpected output is represented by carbon emissions and nonpoint source pollution. Unlike previous studies, this article not only considers the non-expected output of agricultural carbon emissions, but also calculates the non-expected output of agricultural non-point source pollution in the process of farmland utilization, taking into account the typical problem of agricultural non-point source pollution in Hunan Province.

Table 1. Input-output index system of ECLU.

1st indices	2st indices	Variable description
Input indicators	land input	Total planting area of crops (1000 hectares)
	labor input	Employees of agriculture, forestry, animal husbandry, and fishery * (total agricultural output value/total agricultural, forestry, animal husbandry, and fishery output value) (10000 persons)
	fertilizer input	Fertilizer application amount (converted to pure, 10000 tons)
	pesticide input	Pesticide usage (10000 tons)
	plastic sheeting for agricultural use input	Consumption of plastic sheeting for agricultural use (10000 tons)
	agricultural machinery power input	Total power of agricultural machinery (10000 kW)
	irrigation input	Effective irrigation area (1000 hectares)
Expected output indicators	total agricultural output value	Total agricultural output value (100 million RMB)
Unexpected output indicators	carbon emissions	Comprehensive carbon emissions from fertilizer, pesticides, plastic sheeting for agricultural use, agricultural diesel, and agricultural irrigation (10000 tons)
	non-point source pollution	Calculate according to the manual of farmland film residue coefficient, pesticide loss coefficient, and agricultural pollution source fertilizer loss coefficient

The expected output of agriculture is expressed by the total output value of agriculture. Drawing lessons from Yang and Wang (2021) [1], Yin and Hou (2022) [31], this paper selects six indicators to estimate the carbon emissions in the unexpected output of agriculture, including fertilizer, pesticides, plastic sheeting for agricultural use, agricultural diesel, agricultural irrigation, and agricultural cultivation. The emission coefficients of the above six types of emission sources are 0.896 kg/kg, 4.934 kg/kg, 5.180 kg/kg, 0.593 kg/kg, 20.476 kg/ha, and 312.6 kg/ha, respectively. The estimation of agricultural non-point source pollution is based on the Manual of Agricultural Film Residue Coefficient, the Manual of Pesticide Loss Coefficient, and the Manual of Agricultural Pollution Source Fertilizer Loss Coefficient.

Model Setting and Variable Selection

Variable Selection

1. Dependent variable. The explained variable in this paper is the ECLU, which is measured by the SBM model with undesired output and the constant return to scale using the indicator system mentioned above.
2. Independent variable. As the core explanatory variable of this paper, agricultural productive services (APS) refer to the preproduction, mid-production, and post-production services provided for agricultural production, such as agricultural technology services and agricultural means distribution services. With regard to the quantification of agricultural productive services, the existing macrolevel literature mainly measures the development level of agricultural productive services by the proportion of the number of rural employees in the industries related to agricultural productive services to the total number of people. It is obviously inaccurate to use rural employment directly for quantification. Referring to relevant research, this paper selects the output value of agriculture, forestry, animal husbandry, and fishery services/total planting area of crops as the measurement index of the development level of agricultural productive services.
3. Threshold variable. Per capita disposable income (IM), as the threshold variable of this paper, is expressed by the per capita disposable income of rural residents. The larger the per capita disposable income is, the smaller the income constraint of agricultural productive services, and the greater the role of improving the ECLU. The second threshold variable is the cultivated area per capita (pca), which is expressed by the total planting area of crops/total rural population.
4. Control variables. Referring to the literature [52] on the ECLU, and according to the principle of availability of county data, the control variables selected in this paper that affect the ECLU are (1) rural labor transfer (ltrans): select the proportion of nonagricultural employment among rural employees as the agent variable of labor transfer. (2) Grain planting structure (Pstr): agricultural planting structure will have a great impact on agricultural input and output [53], so agricultural planting structure is selected as the control variable. So, the proportion of grain crop sown area in the total crop sown area is selected to measure the grain structure. (3) Irrigation index (Irrigation) is expressed by effective irrigation area/total planting area of crops * 100. (4) The mechanization intensity (Mechanize) is measured by the total power of agricultural machinery/the total planting area of crops * 100. (5) Industrial structure (Istr): research shows that industrial structure has a great impact on the ECLU [54]. For this reason, the variable of industrial structure is selected as the control

variable that affects the ECLU. The industrial structure is expressed by the proportion of added value of secondary and tertiary industries in GDP. To eliminate the influence of heteroscedasticity, all variables are logarithmically processed.

Model Settings

1. Panel quantile regression model

To distinguish counties with different eco-efficiency of cultivated land use, this paper uses a panel data quantile regression model to explore the impact of agricultural productive services. Quantile regression was first proposed by Koenker and Bassett (1978). Compared with ordinary linear regression, quantile regression can select any quantile for parameter estimation, and because quantile regression does not make specific assumptions about the distribution of error terms, its sensitivity to outliers is far less than that of mean regression, and its estimation results are more robust [55, 56].

2. Panel threshold regression model

$$\begin{aligned} \mathrm{ECLU}_{it} = C + C_{11A}APS_{it}(PG_{it} \le \lambda_1) + \\ C_{12}APS_{it}(\lambda_1 < PG_{it} \le \lambda_2) + \cdots \\ +C_{1n-1}APS_{it}(\lambda_{n-1} < PG_{it} \le \lambda_n) \\ + C_{1n}APS_{it}(PG_{it} > \lambda_n) \\ +C_2\mathrm{ltrans}_{it} + C_3\mathrm{Pstr}_{it} + C_4\mathrm{Irrigation}_{it} \\ + C_5\mathrm{Mechanize}_{it} + C_6 Istr_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

Among them, PG is the threshold variable, which represents the per capita disposable income of rural residents or per capita cultivated land area in this paper. $\lambda_1, \lambda_2, \ldots, \lambda_{n-1}, \lambda_n$ is the threshold value within the corresponding threshold range. $C_{11}, C_{12}, \ldots, C_{1n-1}, C_{1n}$ refer to the parameters to be estimated under different threshold intervals.

3. To verify the possible intermediary effect, the intermediary effect model introduced is as follows:

$$\begin{cases} Y_{i,t} = \alpha_1 + \beta_1 Y_{i,t-1} + cX_{i,t} + \varepsilon_{i,t} \\ M_{i,t} = \alpha_2 + \beta_2 M_{i,t-1} + aX_{i,t} + \varepsilon_{i,t} \\ Y_{i,t} = \alpha_3 + \beta_3 Y_{i,t-1} + c'X_{i,t} + bM_{i,t} + \varepsilon_{i,t} \end{cases} \tag{3}$$

where Y is the interpreted variable, X is the explanatory variable, and M is the intermediary variable in Formula 3. β, a, b, c, and c' are the regression coefficients of the corresponding variables, and ε is a random error item. This paper uses the stepwise regression method to test the intermediary effect; that is, when a, b, and c are significant, there is an intermediary effect, and the size of the intermediary effect is $a * b$. If c is significant and at least one of a and b is not significant, then we need to further use the test statistics to test the significance of $a * b$. If $a * b$ is significant, there is an intermediary effect. Furthermore, if c' is not significant in the case of the mediation effect, it means complete mediation; otherwise, it is partial mediation.

Data Source and Descriptive Statistical Analysis

Considering the reality of agricultural development and the availability of data, the sample interval selected in this paper is 2007-2020, and the sample unit is the county-level data of Hunan Province. The main reasons for choosing Hunan Province as the research destination are as follows: firstly, Hunan Province was one of the earliest provinces in China to start pilot agricultural socialized services. Secondly, the agricultural non-point source pollution problem and farmland pollution problem in Hunan Province are the most representative among all provinces in the country. There are a total of 122 counties in Hunan Province. As a major agricultural province,

Table 2. Descriptive analysis of variables.

Variable	Explanation	Unit	Mean	Sd
Eco-efficiency of cultivated land use (ECLU)	Calculate according to the SBM model with two non-consensual outputs of agricultural carbon emissions and non-point source pollution		0.2765	0.1525
Agricultural productive services (APS)	Output value of agriculture, forestry, animal husbandry, and fishery services/total planting area of crops	RMB/mu	1502.63	1617.38
Labor transfer (ltrans)	(1-Number of agricultural employees/number of rural employees) * 100	%	41.85	11.91
Grain planting structure (Pstr)	Sowing area of grain crops/total planting area of crops * 100	%	59.45	8.91
Irrigation index (Irrigation)	Effective irrigation area/total planting area of crops * 100	%	35.31	9.85
The mechanization intensity (Mechanize)	Total power of agricultural machinery/total planting area of crops	Watts/mu	6.46	3.19
Industrial structure (Istr)	Added value of secondary and tertiary industries/GDP * 100	%	80.07	8.39
Per capita disposable income (IM)	Measurement of per capita disposable income of rural residents	RMB/person	9672.95	6214.91
cultivated area per capita (pca)	Total planting area of crops/total rural population	Mu/person	3.91	2.04

Table 3. Estimation results of panel quantile regression model.

Explanatory variable	FE	5%	25%	50%	75%	95%
APS	0.1348*** (15.81)	0.156*** (8.12)	0.135*** (10.40)	0.118*** (8.15)	0.071*** (6.00)	0.070*** (2.85)
ltrans	0.3522*** (7.20)	0.214*** (3.28)	0.218*** (3.92)	0.229*** (4.84)	0.289*** (5.18)	0.625*** (4.09)
Pstr	-1.7166*** (-16.88)	-0.579*** (-7.30)	-0.710*** (-8.06)	-0.92*** (-8.85)	-1.051*** (-9.03)	-1.440*** (-3.95)
Irrigation	-0.1048*** (-2.89)	0.175** (2.42)	-0.01 (-0.18)	-0.097** (-1.89)	-0.124** (-2.04)	0.046 (0.29)
Mechanize	0.3305*** (8.78)	-0.067 (-1.44)	0.018 (0.47)	0.071** (2.28)	0.198*** (2.97)	0.158* (1.68)
Istr	0.7412*** (5.19)	0.206 (1.37)	0.093 (0.59)	-0.147 (-1.12)	-0.415** (-2.22)	-0.697 (-1.54)
constant	4.5480*** (5.74)	1.792*** (2.39)	3.721*** (4.34)	6.148*** (8.06)	8.069*** (9.80)	9.634*** (3.71)

Note: *, * * and * * * represent the significance level of 10%, 5% and 1% respectively. The values in brackets are the values of t statistics, the same below.

Hunan Province is typical. This paper analyzes 97 counties on the basis of eliminating the counties that do not carry out agricultural production. The basic data in this paper is from the Hunan Statistical Yearbook, the Hunan Rural Statistical Yearbook, the statistical yearbook of cities and counties, and the national economic statistical bulletin. The article provides descriptions and statistical analysis of relevant variables (Table 2).

Empirical Results and Analysis

Panel Quantile Regression Model Estimation Results

To verify what conclusions the traditional panel data model in the classical literature will draw, and as a reference result for panel quantile estimation, this paper first selects the fixed effect model estimation result from the panel data. In panel quantile model estimation, five representative quantiles of 5%, 25%, 50%, 75%, and 95% are selected in this paper (Table 3).

First, we should focus on the impact of agricultural productive services on the ECLU. The coefficients of agricultural productive services at both the fixed effect model and the quantile level are positive and have passed the 1% significance level test, which means that since 2007, agricultural productive services at the county level in Hunan Province have significantly promoted the improvement of the ECLU. By observing the change trend of the agricultural productive service coefficient at each quantile level, it is not difficult to find that the coefficient of agricultural productive service has experienced a trend of decline, and the improvement range of ECLU is 0.070~0.156. In terms of the quantile level of different conditions, that is, for the counties with extremely low ECLU, agricultural productive services have a more obvious role. Specifically, for counties with low ECLU, farmers' production processes are still the traditional production mode of ensuring food production by increasing the input of various environmental factors. This is perhaps because the development of the local agricultural productive service market is relatively backwards, and the basic conditions for improving the ECLU cannot be effectively guaranteed, but by improving the level of agricultural productive service in these areas, through the embedding of the "soft input" factor of agricultural productive services, local farmers can optimize the allocation of resources in the agricultural production process, improve the efficiency of resource allocation, solve many bottlenecks in the process of improving the ECLU, and thus achieve the improvement of the ECLU. It should be noted that the coefficient of the agricultural productive service variable in the estimation result of the fixed effect model is 0.1348, which is higher than the regression coefficient at most quantile levels. Other explanatory variables generally have this phenomenon as well. It can be seen that the regression result obtained by the traditional fixed effect model may be overestimated if the heterogeneity problem described is not considered.

Among other control variables, the coefficient of labor force transfer is positive, and all pass the significance test at the level of 1%, which shows that the nonagricultural transfer of the labor force can significantly promote the improvement of the ECLU; that is, the nonagricultural transfer of the rural labor force not only has no negative impact on agricultural production but also has a significant role in promoting agricultural production. Relevant scholars have disputed this issue. Some scholars believe that the impact of labor transfer on agricultural production is negative [57], while other scholars believe that it is positive [58]. The possible reasons for the positive conclusion of this study are that there is a masking effect, that is, technological innovation and institutional

Table 4. Estimation results of double panel threshold regression model.

variable	Threshold variable (IM)	t Stat	Sig	Threshold variable(para)	t Stat	Sig
APS	**0.0771***** (<8.7749)	4.22	0.000	**0.1152***** (<1.0393)	5.25	0.000
APS	**0.1147*****	6.35	0.000	**0.1443*****	6.54	0.000
APS	**0.1571***** (>10.0193)	7.82	0.000	**0.1694** *** (>1.6547)	7.33	0.000
ltrans	0.2557***	3.53	0.001	0.3226***	4.41	0.000
Pstr	-1.3322***	-5.79	0.000	-1.4105***	-5.51	0.000
Irrigation	-0.0927	-1.30	0.198	-0.0698	-0.89	0.378
Mechanize	0.2398***	3.00	0.003	0.2744***	2.93	0.004
Istr	0.1850**	1.91	0.042	0.3393**	1.96	0.036
constant	6.0898***	4.33	0.000	5.0982***	3.19	0.002

innovation offset the negative impact of labor outflow. On the other hand, due to the outflow of the labor force, that is, the reallocation of family labor resources, the input structure of various elements of agricultural input has changed, and with the nonagricultural transfer of the rural labor force, there is a demand for replacing labor with machinery and agricultural productive services, which further releases more rural labor. The development of agricultural productive services has promoted the standardization and industrialization of agricultural production, which not only increases the crop yield but also helps save water, fertilizer, and labor, and improves labor productivity and resource utilization efficiency, thus showing a positive impact on the ECLU, which will be further analyzed later.

Estimation Results of the Panel Threshold Regression Model

Based on the test, it is found that regardless of whether the income level of farmers or the area of cultivated land per person is used as the threshold variable, the test results show that there is a double threshold effect at the 1% significance level, and the triple threshold hypothesis is rejected. As a consequence, the double threshold model is selected for analysis (Table 4).

After confirming the existence of the threshold effect, bootstrapping was performed 500 times. The threshold value is estimated, and the estimated results of the Stata software output are shown in Table 4. It can be seen from the table that when the per capita disposable income of rural residents is taken as the threshold variable, the threshold values corresponding to the double threshold are $e^{8.7749} = 6469.79$ and $e^{10.0193} = 22455.71$, respectively. According to the coefficient corresponding to the threshold value, as the per capita disposable income of rural residents increases, the impact coefficient of agricultural productive services on the ECLU changes from 0.0771 to 0.1147 after crossing the first threshold value. After crossing the second threshold value, the impact coefficient changes from 0.1147 to 0.1571, indicating that as the income level of rural residents increases, the impact of agricultural productive services on the ECLU shows a gradual increasing trend. This further shows that with the increase in rural residents' income, farmers are no longer only concerned about the output of cultivated land but are more concerned about the sustainability of cultivated land development.

When the per capita cultivated area is taken as the threshold variable, the corresponding threshold values are $e^{1.0393} = 2.83$ and $e^{1.6547} = 5.23$. The impact coefficients are 0.1152, 0.1443, and 0.1694, respectively, and they all pass the statistical test at the 1% significance level, indicating that the impact of agricultural productive services on the ECLU gradually increases with the threshold of per capita cultivated land area.

Impact Mechanism

To further analyze the nonlinear impact mechanism of the development of agricultural productive services on the input factors of the ECLU, this paper constructs a panel smooth transformation model (PSTR) of each input factor and agricultural productive services based on the decomposition of the input factors that affect the ECLU. The test results show that there are nonlinear effects. The dependent variables of Models (1), (2), (3), (4), (5), (6), and (7) are agricultural labor input, land input, fertilizer input, pesticide input, plastic sheeting for agricultural use input, agricultural machinery input, and irrigation input (Table 5).

It can be seen that agricultural productive services have a nonlinear relationship with each input factor of ECLU (Table 5). Among them, when the conversion variable is the income level of farmers, the input of labor force (i.e., agricultural practitioners) and pesticides will decrease with the development of agricultural productive services, which is consistent with the above mechanism analysis. In terms of the planting area of crops, after crossing the threshold value, agricultural productive services will effectively increase the planting area of crops; that is, agricultural productive services can significantly reduce

Table 5. Nonlinear impact mechanism.

Model	Conversion variable	APS (Linear part coefficient)	APS (Nonlinear partial coefficient)
Model (1)	income	-0.021*** (-4.26)	-0.006*** (-4.45)
	para	-0.024*** (-5.43)	-0.035*** (-2.68)
Model (2)	income	-0.014*** (-13.20)	0.041*** (8.27)
	para	-0.012*** (-3.79)	-0. 183*** (-6.48)
Model (3)	income	-0.004 (-0.98)	-0.017*** (-5.24)
	para	-0.037*** (-3.45)	0.026*** (2.63)
Model (4)	income	-0.038*** (-6.92)	-0.012*** (-5.30)
	para	-0.037*** (-6.88)	-0.112 (-1.33)
Model (5)	income	-0.006 (-1.14)	0.019 (6.74)
	para	0.022*** (3.71)	-0.090* (-1.75)
Model (6)	income	-0.196** (2.12)	0.178* (-1.93)
	para	-0.023*** (4.07)	0.014** (-2.33)
Model (7)	income	-0.061*** (-9.56)	0.039*** (6.55)
	para	-0.014* (-1.95)	0.040** (6.14)

Note: The values of t statistics are in brackets.

farmers' farmland abandonment and improve farmers' enthusiasm for grain planting [59, 60]. In terms of fertilizer input, when farmers' income level is low, the fertilizer reduction effect of agricultural productive services is not significant, but after crossing the threshold, agricultural productive services agriculture significantly reduce the fertilizer input of farmers. The impact of agricultural productive services on agricultural plastic film input is not significant. Before crossing the threshold, the impact of agricultural productive services on agricultural machinery input and irrigation input is negative, while after crossing the threshold, the impact becomes positive. That is, when the income level of farmers is low, the development of agricultural productive services will reduce and increase the input of agricultural machinery and irrigation, while when the income level is high, it will increase the input of agricultural machinery. The possible reason for this phenomenon is that when the income level of farmers is low, agricultural machinery and irrigation will increase the cost of agricultural production, and farmers will still use the traditional agricultural production mode in the case of uncertain income. However, after crossing the threshold, farmers are less constrained by income. By purchasing agricultural productive services, and in the context of massive labor transfer, mechanized operation and standardized production can effectively replace labor to reduce the possible negative impact, thus increasing agricultural output and achieving the goal of ensuring food production.

When the conversion variable is the per capita cultivated land area, agricultural productive services can effectively reduce labor input, land input, and fertilizer input under certain agricultural outputs. When the per capita cultivated land area is small, agricultural productive services can effectively reduce pesticide input, but after crossing the threshold, the impact of agricultural productive services on pesticide reduction is not significant. The possible reason for this is that with the expansion of the per capita cultivated land area and the large transfer of the rural labor force, the surplus labor force cannot meet the traditional intensive farming production mode. Although agricultural productive service organizations will reduce the amount of pesticide application compared with ordinary farmers through standardized production, the effect of reducing the amount of pesticide to ensure agricultural output has not reached statistical significance.

In summary, we find that agricultural productive services, on one hand, reduce the input of environmental factors, thereby reducing agricultural carbon emissions and agricultural nonpoint source pollution, in other words, reducing undesirable output. On the other hand, under the condition of a certain agricultural output, the unit efficiency of land production can be improved by reducing the input of land and labor, and the impact paths mentioned above have been confirmed.

Robustness Test

Robustness Test of the Quantile Regression Model

To test the robustness of the results of this paper, this paper first focuses on 52 major agricultural production counties in Hunan Province according to the list published by the Ministry of Agriculture and Rural Affairs of the People's Republic of China in the 97 counties in the panel quantile regression model, and in the process of measuring ECLU, changes from constant returns to variable returns to scale. The panel quantile regression model is used to analyze the impact of agricultural productive services on

Table 6. Estimation results of panel quantile regression model.

Explanatory variable	5%	25%	50%	75%	95%
APS	0.186*** (13.75)	0.187*** (9.61)	0.206*** (9.54)	0.182*** (6.37)	0.179*** (3.59)
ltrans	0.205*** (3.01)	0.278*** (3.84)	0.415*** (7.07)	0.647*** (4.47)	0.408 (1.49)
Pstr	-0.325*** (-4.04)	-0.455*** (-4.10)	-0.512*** (-5.32)	-0.861*** (-5.54)	-1.480*** (-3.60)
Irrigation	0.038 (0.35)	-0.286** (-2.24)	-0.527*** (-6.80)	-0.683*** (-4.86)	-0.049 (-0.14)
Mechanize	-0.032 (-0.52)	-0.102* (-1.76)	0.073 (1.23)	0.039 (0.39)	0.055 (0.58)
Istr	0.302* (1.89)	0.414* (1.69)	-0.221 (-0.88)	-0.766** (-2.19)	-0.988 (-1.50)
constant	0.619 (0.76)	1.888 (1.53)	5.001*** (5.75)	8.967*** (5.42)	11.665*** (4.12)

Table 7. Estimation results of robustness test.

Explanatory variable	APS		ltrans	Pstr	Irrigation	Mechanize	Istr	C
	Linear part	Nonlinear partial						
coefficient	0.095***	0.135***	0.248***	-1.514***	-0.097***	0.276***	0.10	7.09***
t Stat	10.53	10.56	5.21	-15.34	-2.82	7.63	0.67	93.27

the ECLU in 52 major agricultural production counties (Table 6).

The results obtained are basically consistent with the model results, indicating that the empirical results of this paper are relatively stable. Through comparison, it can be seen that the impact in large counties is greater. We should encourage major grain-producing counties to vigorously develop agricultural productive services and promote the steady improvement of ECLU.

Robustness Test of Panel Threshold Regression Model

To further test the robustness of the panel threshold regression results, the panel smooth transition regression (PSTR) model is used for the robustness test (Table 7).

It can be seen that after crossing the threshold value, the impact coefficient increases from 0.095 to 0.135, which further indicates that the impact of agricultural productive services on the ECLU is nonlinear, and shows an increasing trend of the impact effect, which is consistent with the previous empirical results. This further proves the robustness of the empirical results.

Further Analysis: Mediating Effect

The Relationship between Agricultural Productive Services and ECLU

Nonagricultural employment is one of the important factors promoting the development of agricultural productive services [61]. Research has shown that the average treatment effect of the treatment group is 0.623 for the probability of farmers observing productive agricultural services, which indicates that the probability of farmers from the labor force who do not include migration significantly reduces by 62.3%. External agricultural productive services have effectively replaced the shortage of labor within the family, ensuring the smooth progress of agricultural production. Since the reform and opening up 40 years ago, the labor cost of agricultural production has been increasing, resulting in the gradual transfer of rural labor from the agricultural sector to the nonagricultural sector. Research indicates that the employment structure of rural labor is dominated by agriculture; however, its proportion is decreasing annually. The development of secondary and tertiary industries significantly contributes to the non-agricultural employment of rural laborers, who transfer mainly to the building, industry, and consumption fields—especially consumption, which has the greatest ability to absorb surplus rural labor [62]. It not only realizes the reallocation of the family labor force structure but also induces agricultural machinery to replace the labor force and alleviate the impact of labor loss on agricultural production [63]. The mechanism and causality of agricultural productive services and labor transfer on the ECLU are questions worthy of in-depth discussion.

Based on this, this paper, using the county data of Hunan Province, explores the logic and causal relationship between agricultural productive services, rural labor transfer, and ECLU by establishing an intermediary effect model. A scientific exploration of the complex relationship between agricultural productive services, rural labor transfer, and ECLU will help objectively recognize the reality of current agricultural production and grasp the direction of the sustainable development of the agricultural economy.

The Intermediary Effect Test of Labor Transfer

First, we will examine whether labor transfer has played an intermediary role in agricultural productive services to promote the ECLU (see Table 8).

Table 8. Test results of intermediary effect of labor transfer.

Explanatory variable	**Regression (1) Explained variable: eco-efficiency of cultivated land use**	**Regression (2) Explained variable: labor transfer**	**Regression (3) Explained variable: eco-efficiency of cultivated land use**
Agricultural productive services	0.1133^{***} (13.56)	0.0428^{***} (7.67)	0.1011^{***} (12.06)
Labor transfer			0.2856^{***} (7.15)
Sobel test statistic		0.0122^{***} (5.231)	
Goodman-1		0.0122^{***} (5.207)	
Goodman-2		0.0122^{***} (5.255)	

Table 9. Test results of intermediary effect of agricultural productive services.

Explanatory variable	**Regression (1)** **Explained variable:** eco-efficiency of cultivated land use	**Regression (2)** **Explained variable:** Agricultural productive services	**Regression (3)** **Explained variable:** eco-efficiency of cultivated land use
Labor transfer	0.3841^{***} (9.33)	0.9735^{***} (7.67)	0.2856^{***} (7.15)
Agricultural productive services			0.1011^{***} (12.06)
Sobel test statistic		0.0983^{***} (6.472)	
Goodman-1		0.0983^{***} (6.457)	
Goodman-2		0.0983^{***} (6.488)	

Agricultural productive services and labor transfer can significantly promote the ECLU (See Table 8). Above all, due to the development of agricultural productive services caused by agricultural labor transfer [64], agricultural productive services first increase the circuitous degree of agricultural production through the professional division of labor and promote the improvement of agricultural total factor productivity [65]. Second, through the substitution effect and the optimization of factor allocation, agricultural productive services can promote the reduced application of pesticides and fertilizers, thereby affecting the ECLU [66]. Agricultural productive services not only directly affect the ECLU but also promote the improvement of the ECLU "partially" through the intermediary variable of labor transfer, accounting for 10.8% of the intermediary effect.

The Intermediary Effect of Agricultural Productive Services

We further test whether agricultural productive services play an intermediary role in promoting the ECLU through labor transfer (see Table 9). From the regression results in Table 9, it can be seen that labor transfer not only directly affects the ECLU, but also "indirectly" promotes the ECLU through the intermediary role of agricultural productive services, which accounts for 25.6%. This result further validates Li Linfei's (2022) view that agricultural productive services can effectively alleviate the possible negative impact of nonagricultural labor transfer on agricultural production [57].

From the perspective of the intermediary effect of agricultural productive services and labor transfer, it can be considered that agricultural productive services and labor transfer complement each other and jointly promote the ECLU.

Discussion

Regarding the research on agricultural productive services, scholars have explored the impact of agricultural productive services on suppressing agricultural carbon emissions [67], promoting agricultural environmental efficiency [2],but its impact on ECLU has not yet been noticed. Improving the ECLU has become an important part of ensuring food security and solving environmental pollution problems. Scholars have focused on research related to ECLU, including land fragmentation, land scale management, labor transfer, and digital inclusive finance [68-71].However, it is worth noting that currently, only a few scholars have included environmental pollution in the evaluation indicators of farmland utilization efficiency. Scholars mainly focus on agricultural non-point source pollution or agricultural carbon emissions in terms of unexpected output related to environmental pollution. For example, Tian Hongyu used a directional distance function to calculate the ECLU from the perspective of unexpected output, including agricultural non-point source pollution [72].Ma Xianlei used the super-efficient SBM model to calculate the ECLU from the perspective of two types of unexpected outputs, including agricultural carbon emissions and agricultural non-point source pollution [73].Unlike the above research, scholars used the transcendental logarithmic stochastic frontier analysis method to calculate the ECLU, which includes agricultural carbon emissions and agricultural non-point source pollution, based on microsurvey data [74, 75]. Referring to relevant literature, this article focuses on unexpected outputs, including agricultural non-point source pollution and agricultural carbon emissions, and uses a super-efficient SBM model with unexpected outputs to calculate ECLU. The difference from previous research lies in firstly, focusing on county-level data in Hunan Province, where agricultural non-point source pollution is the most severe, which is different from previous research on provincial-level panel data or micro survey data. Secondly, previous studies analyzing the impact of agricultural scale management on ECLU did not consider the impact of agricultural productive services on service scale management from the perspective of agricultural division of labor. The impact of agricultural productive services, as the main form of service-scale operation, on the quality protection behavior of farmers' cultivated land cannot be ignored [76]. Therefore, the impact of agricultural productive services on ECLU cannot be ignored.

Based on this, this article delves into the nonlinear impact, impact mechanism, and threshold characteristics of agricultural productive services on ECLU based on measuring the ecological efficiency of cultivated land use. It is a beneficial supplement to existing research, enriches research results in this field, and explores a new path for improving ECLU based on agricultural productive services.

It is worth noting that this study delves into the possible role of labor transfer in the impact of agricultural productive services on ECLU. This strongly explains the potential driving force behind the continuous improvement of ECLU in the current context of a large number of non-agricultural labor transfers in China. This paper not only provides a feasible approach to improving ECLU through agricultural productive services, but also offers valuable insights for other Chinese provinces and developing countries grappling with similar challenges. Given the context of significant labor force migration and the pressures of food security, agricultural product quality, and sustainable agricultural development, investigating ECLU from the perspective of agricultural productive services holds practical and reference value. Future research could expand the scope beyond Hunan Province, consider the cross-regional operations and labor flow of agricultural productive service organizations, and explore spatial spillover effects. Additionally, incorporating micro-level survey data would provide stronger support for the research conclusions.

Conclusions and Recommendation

This paper analyzes the impact of agricultural productive services on the ECLU in Hunan Province, using panel data from 97 counties spanning 2007 to 2020. Various models, including panel quantile regression, panel threshold regression, panel smooth transition, and intermediary effect models, are employed to explore the mechanism and pathway of this impact. The key findings are as follows:

1. Panel quantile regression shows that agricultural productive services significantly increased the ECLU of each county, and as ECLU increased, the impact effect of agricultural productive services gradually decreased.
2. The impact of agricultural productive services is nonlinear, constrained by farmers' income levels and per capita cultivated land size. As income levels and land area increase, the promotion effect gradually increases.
3. The pathway through which agricultural productive services affect ECLU primarily involves reducing environmental inputs such as pesticides and fertilizers, leading to a reduction in undesirable outputs.
4. In addition to direct promotion of ECLU, agricultural productive services indirectly enhance it by facilitating labor transfer, with an indirect effect accounting for 10.8%.

Research has shown that agricultural productive services can, to some extent, promote the improvement of ECLU. Therefore, in the future, China should continue to vigorously promote the development of agricultural productive service organizations, cultivate diverse service entities, and enable them to provide targeted and differentiated agricultural productive services based on the resource endowment of different types of farmers in order to better play the driving role of agricultural productive services in driving green and low-carbon development of arable land. Secondly, China will still face the main form of small-scale farmer operation. Agricultural productive service organizations should focus on small-scale farmers to serve their goals, and drive them to engage in farmland protection behavior through service involvement, driving them to embark on a modern path of green and low-carbon development.

Acknowledgements

This research was funded by the Project of Hunan Provincial Social Science Achievement Review Committee, topic name: The adoption behavior of ecological planting and breeding technology under the aging of rural areas – based on the theory and demonstration of rice-fish coculture, grant number XSP2023GLC108. This research was funded by the Project of the Research Foundation of Education Bureau of Hunan Province,China.Topic Name: Mechanism, Effects, and Road Strength Optimization of Agricultural Productive Services Driving Green and Low Carbon Development in Agriculture.(Grant No.23B0819).

Conflict of Interest

The authors declare no conflict of interest.

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