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The Impact of Rural Population Aging on the Development of Green Agricultural Technology: A Spatial Perspective Study

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Abstract: Promoting the green development of agriculture is an essential path toward modernizing agriculture in China, while the regional aging of the rural population structure poses new challenges to green agricultural development. Based on the spatial error model (SEM) and the perspective of human capital level, this paper uses the SBM-ML index method to construct the level of green agricultural development and empirically analyzes the impact of rural population aging on green agricultural development. The study finds that both an increase in the proportion of the rural elderly population and an increase in the old-age dependency ratio restrain green agricultural development. Additionally, the aging of the rural population has a negative impact on the level of rural human capital. Robustness analysis using replacement weight matrices confirms the reliability of the paper's conclusions. Therefore, efforts are needed to enhance rural education levels, provide more training opportunities for rural elderly individuals, and promote the dissemination of green agricultural technologies to facilitate rural green development.

Keywords: Green agricultural total factor productivity; Rural population aging; Spatial error model; Human capital level

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1. Introduction

In recent years, the issue of population aging in China has become increasingly prominent. According to data from the seventh national census, the population aged 60 and above has reached 264.02 million, with 190.64 million people aged 65 and above, accounting for 13.5% of the total population. In rural areas, the proportion of individuals aged 60 and above has risen to 20.04%, and those aged 65 and above account for 13.82% (Data source: Comprehensive Research Report on Rural Revitalization in China 2021). The aging population structure in China, especially in rural areas, poses unprecedented challenges to agricultural production methods, which has become a pressing issue for China's agricultural development.

The impact of changes in the rural population structure on agricultural development in China primarily focuses on the following aspects.

The aging rural population in China affects agricultural production in both positive and negative ways. While it decreases grain output and hinders labor-intensive agriculture, it can also promote mechanization and large-scale farming [1–3]. Scholars have explored the impact of aging on agricultural efficiency, with some suggesting that elderly farmers' traditional knowledge supports green agriculture, while others argue that aging hinders the adoption of green technologies and lowers productivity [4–5]. Bao noted that aging reduces the labor supply, weakening production efficiency [6]. Physical limitations further hinder new method adoption, increasing environmental strain [7]. Cooperation between older and younger farmers may mitigate some negative effects [8]. Theoretical views also vary: Hou highlighted the value of elderly farmers' ecological knowledge for sustainable farming, while Zhang argued that aging reduces human capital quality, hindering modernization [9–10]. Gao noted barriers in adopting new technologies, and Li suggested family farming models could combine elderly experience with youth innovation to support green development [11–12].

Rural population aging in China impacts green agricultural development both positively and negatively. Aging reduces labor's ability to adopt new technologies, lowering productivity and quality. The outflow of young workers to cities further diminishes the rural labor force, which hinders green agriculture progress. This study explores the spatial effects of aging on agriculture and the role of human capital in this process.

2. Model specification and variable selection

2.1. Model specification

This paper primarily analyzes the impact of the rural population aging on green agricultural development in China. Considering the main factors influencing green agricultural development, the following baseline model is constructed:

$$gtfp_{it} = \alpha_0 + \alpha_1 old_{it} + \alpha_2 var_{it} + \varepsilon_{it} \tag{1}$$

The dependent variable $gtfp_{it}$ represents green agricultural development. The core explanatory variable old_{it} represents population aging, and var_{it} represents other control variables, which mainly include urbanization level (urb), industrial structure (ind), disaster-affected crop area (dis), planting structure (stru), agricultural infrastructure (infra), and rural social retail sales (sale). ε_{it} denotes the random disturbance term.

Considering that the agricultural population aging in one region may impact agricultural development in surrounding areas, neglecting spatial correlation may lead to inconsistent parameter estimates in empirical analysis. The spatial error model (SEM) introduces a spatial weight matrix W and a spatial error autocorrelation coefficient $\lambda_{2,}$ constructing a spatial autocorrelation structure in the error term. Thus, SEM can explain the relationship between the explanatory variables and the dependent variable and reveal hidden spatial dependency patterns in the data. Therefore, this paper constructs a spatial error model (SEM) for empirical analysis. The SEM considers only the spatial lag of the error term, and its expression is:

$$gtfp_{it} = \beta_0 + \beta_1 old_{it} + \beta_2 var_{it} + \lambda W \varepsilon_{it} + u_{it} \tag{2}$$

Where $\lambda W \varepsilon_{it}$ represents the spatial lag of the error term, λ denotes the spatial error autocorrelation coefficient.

A larger λ indicates a stronger spatial correlation induced by the spatial error terms.

Moreover, to examine whether rural population aging affects green agricultural development through its influence on agricultural human capital levels, this study constructs the following model:

$$hc_{it} = \gamma_0 + \gamma_1 old_{it} + \gamma_2 var_{it} + \lambda W \varepsilon_{it} + u_{it} \quad (3)$$

2.2. Variable Selection

Dependent Variable: Green agricultural Development (gtfp). This study measures green agricultural development using the Malmquist-Luenberger (ML) index to assess green agricultural total factor productivity. This variable describes changes in agricultural production efficiency and environmental sustainability. An increase in $gtfp_{it}$ indicates that while enhancing agricultural economic growth, environmental damage has been reduced, thereby alleviating environmental resource pressures, increasing primary sector income, and achieving coordinated and sustainable development between agriculture and ecology.

First, input variables are defined as follows. (1) Agricultural labor input is measured by the number of people employed in the primary sector; (2) Land input is represented by the sown area; (3) Machinery input is quantified by the total power of agricultural machinery; (4) Fertilizer input is assessed by the effective quantity of fertilizer applied; (5) Irrigation input is indicated by the area with effective irrigation.

The output variables are as follows: (1) Desirable output is primarily measured by the total value of agricultural, forestry, animal husbandry, and fishery products adjusted to constant prices; (2) Undesirable output is represented by agricultural carbon emissions as a proxy variable for undesirable outputs.

Core explanatory variables: Rural population aging (old1) is measured by the proportion of elderly individuals aged 65 and above within the rural population. This study also employs the elderly dependency ratio (old2) for robustness checks. Mechanism variable: Human capital level (lnhc). Control variables: Urbanization level (urb); Industrial structure (ind); Crop disaster area (dis); Cropping structure (stru) I; Agricultural infrastructure (lninfra); Rural social retail sales (lnsale).

2.3. Variable selection and data sources

Due to data availability, this study selects panel data from 30 provinces and municipalities in China (excluding Hong Kong, Macau, Taiwan region, and Tibet) for the period 2007–2020 as the research sample. Minor missing data is addressed using interpolation methods. Data sources include the China Statistical Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook, and the EPS database. The impact of heteroscedasticity is mitigated by taking the natural logarithm of some variables. Descriptive statistics for each variable are presented in **Table 1**.

3. Empirical analysis

3.1. Spatial correlation analysis

Before conducting the spatial econometric analysis, it is necessary to test the spatial autocorrelation of the explained variable. This study employs the Local Moran's I index to examine the spatial autocorrelation of green agricultural total factor productivity. The Moran's I index ranges between -1 and 1; a positive value indicates a positive spatial correlation in green agricultural total factor productivity, a negative value indicates a negative spatial autocorrelation, and a value of 0 indicates no correlation. For spatial autocorrelation and empirical analysis, this study uses a 0-1 adjacency matrix and a distance inverse matrix for robustness checks. Combining formulas (1) and (2), the spatial autocorrelation test of green agricultural development levels across 30 provinces and municipalities in China (excluding Hong Kong, Macau, Taiwan region, and Tibet) is performed using Stata 15.0. The results are presented in **Table 2**.

Table 1. Descriptive statistics of variables

Variable	Obs	Mean	Std.Dev.	Min	Max
gtfp	420	1.085	0.198	0.339	2.949
old1	420	0.115	0.0364	0.0502	0.261
old2	420	16.57	5.981	7.050	44.56
lnhc	420	2.036	0.0848	1.743	2.293
lninfra	420	7.260	1.026	4.693	8.729
lnsale	420	8.382	1.020	5.291	10.36
dis	420	0.186	0.141	0.00592	0.695
urb	420	0.563	0.134	0.282	0.896
ind	420	0.446	0.087	0.158	0.615
stru	420	0.348	0.135	0.029	0.672

Table 2. Spatial autocorrelation analysis of green agricultural total factor productivity (2010–2020)

Variables	Year	Moran'sI
gtfp	2010	-0.017
gtfp	2011	0.03*
gtfp	2012	0.046*
gtfp	2013	0.195*
gtfp	2014	0.012
gtfp	2015	-0.011
gtfp	2016	0.180***
gtfp	2017	0.004
gtfp	2018	0.05
gtfp	2019	-0.021
gtfp	2020	0.056*

Notes: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$

As shown in **Table 2**, between 2010 and 2020, half of the years strongly reject the null hypothesis of "no spatial autocorrelation" at the 1%, 5%, and 10% significance levels, and more than half of the years have positive Moran's I indices. Additionally, previous research indicates that global autocorrelation has significant limitations, so anomalous spatial correlation levels in a few years do not negate the existence of spatial correlation. Therefore, there is spatial autocorrelation in agricultural green total factor productivity, and it is necessary to employ spatial econometrics for subsequent empirical analysis.

3.2. Spatial model selection: First item

First, the spatial econometric model is selected using the Lagrange Multiplier (LM) test, which indicates that the spatial error model is more statistically significant than the spatial lag model, leading to its selection for empirical analysis. Second, the Hausman test reveals a significant *P*-value at the 1% level under the 0-1 spatial weight matrix, prompting the use of fixed effects. Third, the LR test shows that the *P*-values are not significant, supporting the hypothesis that the SDM model degenerates into the SEM model, which further confirms the suitability of the spatial error model. Finally, the time and regional fixed effects model provides the highest maximum likelihood value, thus, the spatial error model with both time and regional fixed effects is employed for the econometric analysis.

3.3. Benchmark regression analysis

Table 3 presents the regression analysis of the impact of rural population aging on green agricultural development from 2010 to 2020. Column (1) shows the effect of population aging on green agricultural development without control variables. It can be observed that the coefficient for rural population aging is negative but not significant. Column (2) gradually introduces control variables, and the coefficient for rural population aging remains negative but is still not significant. In Column (3) of **Table 3**, after including the spatial weight matrix and both time and regional fixed effects, the impact of rural population aging on green agricultural total factor productivity is negative and significant at the 10% level. As discussed earlier, incorporating the spatial matrix makes the regression results more reliable. Therefore, as the degree of population aging increases, green agricultural total factor productivity is suppressed, indicating that the rising proportion of elderly people in the rural population has a negative impact on green agricultural development.

Table 3. Regression results of rural population aging on green agricultural development (2010–2020)

	(1)	(2)	(3)
old1	-0.400	-0.813	-1.419*
	(-1.51)	(-1.22)	(-1.87)
dis		0.003	0.050
		(0.03)	(0.59)
urb		0.022***	0.019***
		(4.27)	(3.51)
ind		0.001	-0.001
		(0.39)	(-0.40)
stru		0.003	0.004
		(1.11)	(1.14)
lninfra		-0.288***	-0.273***
		(-2.81)	(-2.69)
lnsale		-0.219***	-0.185**
		(-3.86)	(-2.44)
_cons	1.131***	3.687***	
	(35.40)	(4.53)	

Table 3 (Continued)

	(1)	(2)	(3)
Spatial			
lambda			-0.580***
			(-3.14)
Variance			
sigma2_e			0.028***
			(14.31)
Time			YES
Area			YES
N	420	420	420

Note: The figures in parentheses represent the standard errors of the regression coefficients. $*P < 0.1$, $**P < 0.05$, $***P < 0.01$

3.4. Robustness checks

This study employs two methods to conduct robustness checks to ensure the reliability of the empirical results. The first method involves replacing the core explanatory variable, with rural population aging being measured by the rural elderly dependency ratio (old2). The second method uses the inverse distance matrix to replace the 0-1 adjacency matrix for spatial econometric analysis. The results are presented in **Table 4**. According to Columns (1) and (2) of **Table 4**, the elderly dependency ratio has a negative impact on both green agricultural development and rural human capital levels. In Columns (3) and (4) of **Table 4**, the use of the inverse distance matrix for spatial econometric analysis still shows a negative impact of rural population aging on green agricultural development and rural human capital levels. Therefore, the results of this study are robust.

Table 4. Robustness checks

	(1)	(2)	(3)	(4)
Dependent Variable	gtfp	lnhc	Gtfp (Inverse Distance Matrix)	Lnhc (Inverse Distance Matrix)
Main				
old2	-0.009*	-0.004***		
	(-1.94)	(-8.56)		
old1			-1.674**	-0.638***
			(-2.22)	(-7.89)
Spatial				
lambda	-0.578***	-0.415**	-0.776***	-0.806***
	(-3.13)	(-2.40)	(-3.47)	(-3.60)
Variance				
sigma2_e	0.028***	0.000***	0.028***	0.000***
	(14.31)	(14.40)	(14.23)	(14.22)
Time	YES	YES	YES	YES
Region	YES	YES	YES	YES
N	420	420	420	420

Note: The figures in parentheses represent the standard errors of the regression coefficients. $*P < 0.1$, $**P < 0.05$, $***P < 0.01$.

4. Summary and recommendations

The authors should discuss the results and how they can be interpreted from the perspective of previous studies and the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

4.1. Research conclusions

The results of this study indicate that rural aging negatively affects both green agricultural productivity and human capital levels, with the reduction of human capital being the key mechanism. Robustness checks confirm that the elderly dependency ratio also suppresses both green agricultural development and human capital. This research contributes to the current literature by exploring how aging influences green agricultural development, a perspective that has rarely been addressed in existing studies.

4.2. Managerial implications

To address the rural population aging and promote green agricultural development, several measures can be taken. First, enhance rural education by increasing investments in infrastructure and establishing training programs on green agricultural technologies to equip farmers with necessary skills. Second, promote green agricultural technologies through pilot demonstration projects, elderly-friendly farming models, and diverse dissemination channels like digital platforms and traditional media. Third, improve elderly farmers' practical skills by organizing on-site expert guidance and developing flexible employment arrangements to match their capabilities. Lastly, guide rational resource allocation through tailored regional development plans and incentives for young talent to work in aging rural areas, improving local economies and balancing labor distribution.

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Author contributions

Study idea conceptualization: Yijuan Xu
Experimentation: Zhenping Xu
Data analysis and paper writing: Yijuan Xu

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