ORIGINAL ARTICLE

Increasing overall agricultural productivity in the Yellow River Delta Eco-economic Zone in China

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Abstract

Improving the efficiency of agricultural production in infertile areas contributes to reducing hunger, ensuring food security, and promoting eco-economic development. This study examines the effects and mechanisms of the Yellow River Delta High Efficiency Ecological Economic Zone policy on agricultural total factor productivity. The data from prefecture-level cities and a difference-in-difference model were used, and descriptive statistics and multiple regression analysis were conducted. The results show that the establishment of the zone increased agricultural total factor productivity by 40%. Heterogeneity analysis reveals that this positive effect is particularly pronounced in regions with a high proportion of agriculture and high per capita disposable income. However, this effect has diminished year by year since 2010. Mechanism tests suggest that the increase in agricultural R&D, the improvement in mechanization, and the application of ecological technologies have boosted agricultural total factor productivity. The results confirm the positive effects of the ecological economic zone policy and highlight the need for further measures to maintain and increase these positive effects in the long term. Future research should explore specific micro-management and technological measures to improve agricultural performance.

Keywords Ecological economic zone · Agricultural total factor productivity · R&D investment · Ecological technologies

Introduction

Improvements in agricultural total factor productivity can stabilize the supply of agricultural products, particularly food, which helps address the global problem of hunger (Barrett 2021; Giller et al. 2021). In addition to advances in production technology and agricultural subsidies (Bernini and Galli 2024), local environmental and economic policies are also important factors influencing changes in agricultural production efficiency (Naeem et al. 2023). Therefore, many countries emphasize the implementation of environmental and economic policies to improve the regional ecosystem for sustainable agricultural growth (King et al. 1988).

China also implemented a national ecological economic zone policy in 2009. On November 23, 2009, the central government officially approved the "Development Plan for the High Efficiency Ecological Economic Zone in the Yellow River Delta," marking the formal establishment of the Yellow River Delta High Efficiency Ecological Economic Zone, which is located in the northwest of Shandong Province and covers the entire Yellow River Delta. A notable feature of this region is that more than 70% of its arable land is saline-alkaline land, which is the largest in China and also one of the most difficult saline-alkaline lands in the world to develop and utilize (Mao et al. 2022). Due to the high content of substances such as sodium chloride, sodium sulfate, and sodium carbonate in saline-alkaline soils, plants face negative impacts on water absorption, nutrient uptake, and growth metabolism (Zhou et al. 2022). Furthermore, outdated production technologies have jointly led to the deterioration of the agricultural environment and low production efficiency (Zhang et al. 2024).

In fact, the ecological economic zone policy in the Yellow River Delta is a regional environmental economic strategy

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aimed at developing ecological agriculture and green economy. As agricultural total factor productivity is a key indicator of agricultural development (Donmez et al. 2024), it naturally raises a question: does the ecological economic zone policy in the Yellow River Delta improve the local agricultural total factor productivity? However, there is still a lack of literature directly addressing this question.

Reviewing the existing literature, agricultural total factor productivity can be divided into two broad categories. The first category focuses on the measurement methodology (Hosseinzadeh et al. 2022). There are non-parametric and parametric methods. Nonparametric approaches mainly include data envelopment analysis (DEA) and the Malmquist Productivity Index (Dias and Helmers 2001). DEA is a linear programming-based technique for evaluating the efficiency of decision units (e.g., farms) against a best-practice frontier. This method assumes the same scale of production for all units, does not require a predetermined functional form of the production function, and can handle multiple inputs and outputs (Mao and Koo 1997). However, its results can be affected by sample selection. For example, in agriculture, the scale of production varies from farm to farm. Using DEA could lead to biased measures due to these differences (Rudi et al. 2012). The Malmquist Productivity Index measures changes in productivity by comparing changes in production frontiers at different points in time. It can be decomposed into efficiency change and technological change components and is suitable for analyzing time series data (Munisamy and Arabi 2015).

Parametric approaches include production function estimation and stochastic frontier analysis (SFA). Production function estimation specifies a particular functional form of the production function, such as Cobb–Douglas or Translog, and estimates its parameters using statistical methods such as ordinary least squares (Gechert et al. 2022). Although this method provides elasticity estimates for production factors, its limitation lies in the assumption that the chosen functional form may not fully reflect real-world conditions (Li et al. 2016; Baker et al. 2020). In contrast, SFA predetermines the form of the production function and introduces a stochastic error term to capture variations in production efficiency (Greene 2005). This allows SFA to distinguish between technical inefficiency and random disturbances for a more accurate measure of production efficiency, an advantage over DEA (Gong 2018). While each method has its own characteristics and limitations, SFA is most commonly used because of its accuracy.

The second category focuses on the factors that affect agricultural productivity (Collier and Dercon 2014). These factors include four broad categories.

The first is technological advancement and innovation, which is one of the key factors in improving agricultural production efficiency (Qayyum et al. 2023; Shah et al. 2023). This includes seed improvement, agricultural mechanization, and improvements in irrigation and fertilizer application techniques (Anser

et al. 2023). These measures not only increase crop yields and improve product quality, but also reduce production costs through large-scale production, thereby improving production efficiency (Pronti et al. 2024). In developing countries, a 1% increase in technological capital leads to an increase in agricultural total factor productivity of about 13% (Dias Avila and Evenson 2010). The average annual growth rate of agricultural output in the UK from 1967 to 1990 was 1.9%, largely due to the widespread adoption of organic technologies (Thirtle and Bottomley 1992). Nearly 20% of the growth in world agricultural output since 1965 has been attributed to technological progress (Fan and Pardey 1997).

The second is the efficiency of resource allocation. Effective resource allocation ensures the optimal use of production factors such as land, labor, capital, and technology in agricultural production (Chavunduka et al. 2021). There is a positive correlation between financial inclusion and the growth of agricultural productivity, and financial inclusion improves agricultural productivity by providing credit to farmers to support the transformation towards specialization and cooperation in production (Hu et al. 2021). During the early stages of reform and opening up, the rapid growth of China's agricultural total factor productivity was mainly driven by the implementation of the household responsibility system and agricultural market reforms (Lin 1992). The market-oriented reform attracted commercial capital to participate in the production, circulation, and sale of agricultural products (Satpathy et al. 2017).

The third is the natural environment. Natural conditions such as climate change, soil quality, and water resources directly affect the agriculture development. For example, under similar conditions, crops typically yield more on fertile land than on barren land (Golla 2021). Another typical manifestation is that air and water pollution can significantly reduce agricultural output. Every 1% increase in PM2.5 levels is associated with a 1.7% decrease in agricultural output (Loftus et al. 2015).

The fourth category includes regional environmental and economic policies, which is the scope of this study. Adaptive environmental management policies are critical to mitigate the adverse effects of the natural environment and to increase the resilience of agricultural systems (Schlenker and Roberts 2009). This is because these policies can increase technology, capital, and other production inputs (Masud et al. 2017). For example, China has implemented rainwater harvesting policies in desert fringe areas, where local governments establish rainwater harvesting systems to increase water resource utilization, which provides additional water sources for agricultural production and increases agricultural production levels (Li et al. 2015). Israel has implemented recycled water and desalination policies for agricultural production, using treated recycled water and desalinated seawater for irrigation (Becker et al. 2010). The Netherlands has improved land drainage systems to effectively manage soil

salinity in saline-alkaline soils and prevent adverse effects of salinity on crops (Ondrasek and Rengel 2021).

In essence, the eco-economic zone policy falls under the category of regional environmental economic policies, which theoretically can affect agricultural productivity. However, research on the Yellow River Delta High Efficiency Ecological Economic Zone has mainly focused on discussing the environmental impacts (Irfan et al. 2020). Since the establishment of the eco-economic zone, there has been no significant reduction in carbon emissions in the Yellow River Delta region (Sun et al. 2014). Industrial energy consumption remains the largest sector contributing to carbon emissions, which means that the policy has not changed the trend of environmental degradation (Song et al. 2023). Total energy consumption in the Yellow River Delta region in 2015 and 2020 was 1.62 times and 2.22 times higher than in 2009, respectively (Wang et al. 2018). However, several studies have found that the optimization of land use patterns in the Yellow River Delta has reduced carbon emissions, indicating that the positive environmental impacts are becoming apparent (Wu et al. 2022).

While the environmental impacts of the Yellow River Delta High Efficiency Ecological Economic Zone have been widely discussed (Gao et al. 2023), there is a notable gap in empirical studies on its economic impacts on agricultural productivity. This study aims to fill this gap, estimate the impact of the policy, and provide valuable policy implications for agricultural development.

This study evaluates the impact of ecological economic zone policy on agricultural total factor productivity. We calculated the agricultural total factor productivity indicator using the SFA model, and then conducted a multivariate regression analysis using the difference-in-difference model. Our research focuses on three main questions: (i) What is the impact of the ecological economic zone policy on agricultural TFP? (ii) If there is an impact, is there heterogeneity in the impact of the policy in areas with high agricultural shares and high per capita disposable income? (iii) What are the pathways of policy impact?

Materials and method

The study area is shown in Fig. 1. The Yellow River Delta High Ecological Economic Zone is located in the northwest of Shandong Province, spanning from 35° to 37° north latitude and from 118° 30′ to 120° 30′ east longitude. This zone encompasses 19 counties across six cities: Dongying, Binzhou, Leling, and Qingyun in Dezhou; Gaoqing in Zibo; and Shouguang, Hanting District, and Changyi in Weifang, as well as Laizhou in Yantai. The total area is approximately 26,500 km2, of which 4657.07 km^2 are saline-alkali soil, accounting for 78.58% of Shandong Province's total saline-alkali land area. The region's topography is uniformly plain, formed by the sediment deposition from the Yellow River.

The implementation of the policy can be considered as a quasi-natural experiment; we adopted the difference-in-difference (DID) model to estimate the policy's impact. Compared to ordinary least squares, the DID model greatly reduces endogeneity problems. Moreover, the DID model can mitigate the potential influence of omitted variables on the results.

All prefecture-level cities in Shandong Province are divided into two groups. The cities of Dongying, Dezhou, Binzhou, and Zibo, which are located in the core area of the Yellow River Delta High Efficiency Ecological Economic Zone, are defined as the treatment group; other cities are defined as the control group. It should be noted that Weifang and Yantai are excluded from the treatment group because their areas within the zone are relatively small. Although the zone was established on November 23, 2009, there is a time lag between the implementation of the policy and its effects. Therefore, we define the time of occurrence of the policy as 2010. The empirical model is set up as follows.
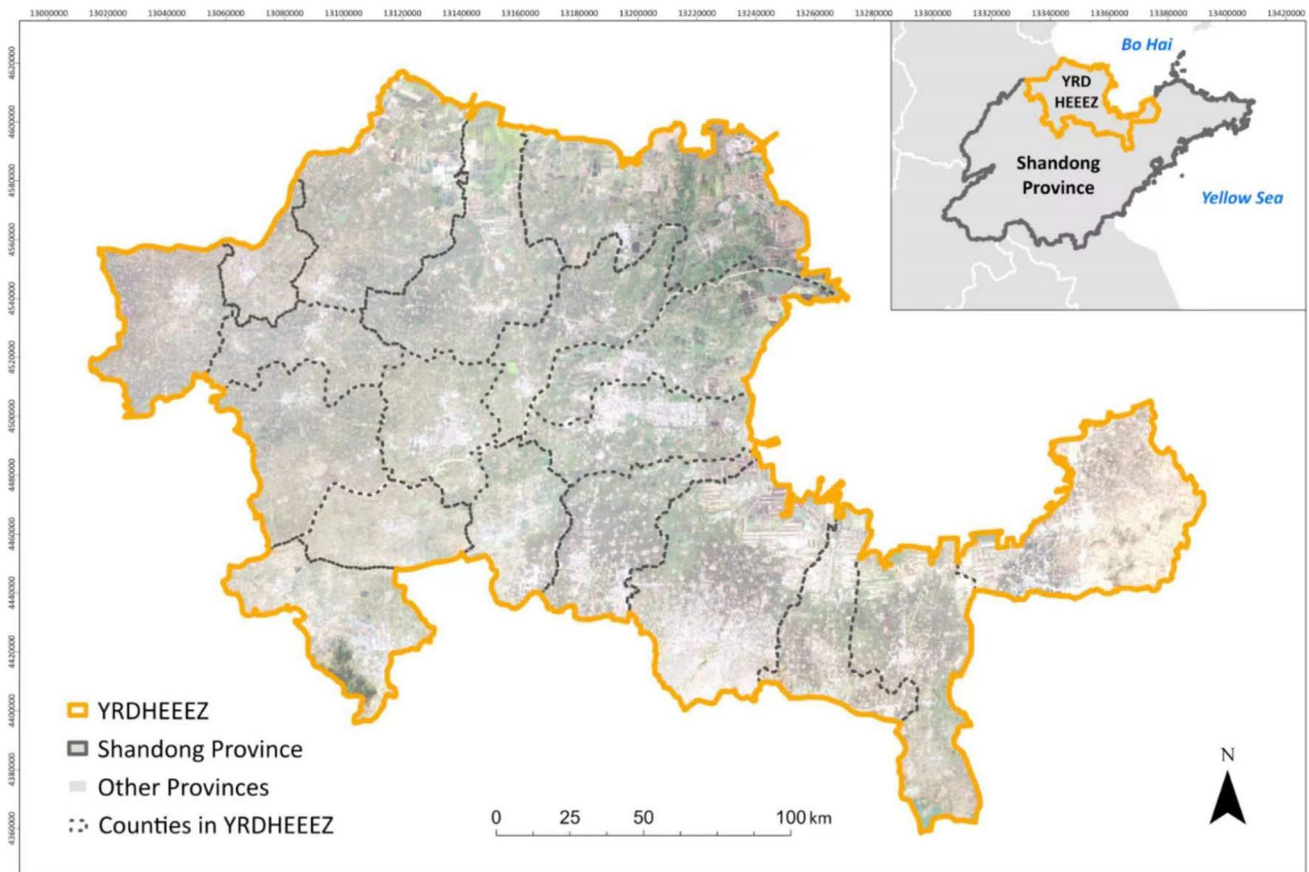
$$TFP_{it} = \alpha + \lambda_1 du + \lambda_2 dt + \lambda_3 policy + \beta X_{it} + \gamma_t + \mu_i + \varepsilon_{it}$$
(1)

TFP_{it} denotes the agricultural total factor productivity of city "i" in year "t", and du is the dummy group variable, if a city belongs to the treatment group, then du equals 1, otherwise, 0. In addition, dt is the time dummy variable, dt = 1 for 2010–2021, and dt = 0 for 2004–2009. The DID term policy is a dummy variable equal to du×dt; the coefficient of policy is our research interest to capture the effect of policy on agricultural productivity. X is a set of control variables, such as the share of primary industry in GDP, foreign direct investment, and farmers' disposable income, and γ_t and μ_i are the city and year fixed effects, respectively. Parameter ε_{it} is random error term.

Following Greene (2005) and Gong (2018), this study used the SFA method to estimate agricultural total factor productivity. The main reason for choosing this method is that the scale of agricultural production varies from city to city. By setting the production function as a transcendental logarithmic production function in stochastic frontier analysis, it effectively avoids the disturbance of random error terms in total factor productivity due to differences in production scale (Gong 2018). The output variable is the value added of the primary industry, calculated at constant prices in 2003. The input variables include the number of agricultural workers, land (sown area), and capital (total output of agricultural machinery). The model is as follows.

$$In\ Y_i = \beta_0 + \beta_1 InL_{it} + \beta_2 InK_{it} + \beta_3 t$$
$$+ 1/2\beta_4 \left(InK_{it}\right)^2 + 1/2\beta_5 \left(InL_{it}\right)^2 + 1/2\beta_6 t^2$$
$$+ \beta_7 InK_{it} nL_{it} + \beta_8 tInL_{it} + \beta_9 tInK_{it} + v_{it} + \mu_{it}$$

$$\mu_{it} = \left\{\mu_{it} exp[\eta(t - T)]\right\} \sim iidN^+\left(\mu, \sigma^2\right)$$
(2)

Fig. 1 The location of the Yellow River Delta High Efficiency Ecological Economic Zone. Source: Ministry of Natural Resources of the People's Republic of China. https://www.mnr.gov.cn/

Y, L, and K represent the per-unit land agricultural output, per-unit land labor input, and per-unit land capital input of prefecture-level cities, respectively, whereas v_{it} denotes the random disturbance, assumed to follow a normal distribution, while the technological inefficiency term and μ_{it} follow a truncated half-normal distribution. The two terms are mutually independent. η denotes the time-varying parameter for the level of technical efficiency.

The sample consists of 16 prefecture-level cities in Shandong Province, covering the period from 2004 to 2021. The decision to exclude data from 2003 and earlier is based on two reasons. First, when evaluating policy effects using the DID model, it is advisable not to keep the time span too long to avoid increasing the likelihood of other policy interventions affecting the results. Second, the statistical standards for pre-2004 data are different from those for post-2004 data. Our research was conducted at the prefecture-level city scale. This is because, in China, data records for county-level cities are incomplete, and statistical standards vary across county-level cities, making it difficult to use data for these cities. The data for calculating agricultural total factor productivity, such as agricultural output per unit of land, labor input per unit of

land, capital input per unit of land, and total land area, were obtained from the China Urban Statistical Yearbook, which is compiled by the National Bureau of Statistics of China based on field surveys. All data on control variables, including the share of primary industry in GDP, foreign direct investment, farmers' disposable income, and the degree of economic openness, were obtained from the Shandong Statistical Yearbook. Descriptive statistics of the variables are presented in Table 1.

Results

Baseline regression

In the study, the difference-in-difference model was used for analysis. The results of column (1) in Table 2 show that the policy increased the agricultural total factor productivity by 38%. Furthermore, by adding control variables, the positive effect increased up to 40.4% and is still significant at the 1% level, as shown in column (2) of Table 2.

This positive impact is closely related to the support measures taken by government. First, to promote the

Table 1 Definition and statistical characteristics of variables, the values in parentheses are standard errors

Variable	Definition	Mean and standard deviation		
		Full sample	Treatment group	Control group
Panel A: dependent variables				
TFP	Agricultural total factor productivity, measured using SFA method	1.42 (0.82)	1.47 (0.84)	1.40 (0.81)
ZLV	The growth rate of total agricultural output value	0.08 (0.09)	0.09 (0.08)	0.08 (0.09)
Panel B: DID variables				
du	1 for cities in treatment group, otherwise 0	0.25 (0.43)	1 (0)	0 (0)
dt	1 for 2010–2021, otherwise 0	0.78 (0.42)	0.78 (0.42)	0.78 (0.41)
policy	DID term, equals du×dt	0.19 (0.40)	0.78 (0.42)	0 (0)
Panel C: channel variables				
ratio_keji	Agricultural R&D, measured by the ratio of agricultural R&D to fiscal expenditure	0.18 (0.01)	0.02 (0.01)	0.01 (0.01)
diesel	Mechanization, measured by the natural logarithm of diesel fuel consumption per $10,000 of agricultural output	3.20 (0.82)	3.53 (0.68)	3.09 (0.83)
fertilizer	Fertilizer application, measured by the natural logarithm of fertilizer consumption per $10,000 of agricultural output	2.04 (0.62)	2.03 (0.64)	2.04 (0.62)
pesticide	Pesticide application, measured by the natural logarithm of pesticide consumption per $10,000 of agricultural output	5.43 (0.65)	5.23 (0.60)	5.50 (0.65)
Panel D: control variables				
rag	The proportion of primary industry in GDP	0.09 (0.45)	0.07 (0.04)	0.10 (0.05)
lnsal	The natural logarithm of farmers' disposable income	2.31 (0.56)	2.29 (0.54)	2.31 (0.57)
lnfdi	The natural logarithm of foreign direct investment	12.51 (1.17)	12.02 (0.61)	12.67 (1.26)
ratio_trade	The proportion of total import and export value to GDP	0.29 (0.27)	0.22 (0.12)	0.31 (0.30)
ratio_invest	The proportion of agricultural expenditure to fiscal expenditure	0.05 (0.05)	0.04 (0.04)	0.05 (0.05)
Observation	Number of observations	288	72	216

research and development of new agricultural technologies, Shandong Province has established the Yellow River Delta Industry Investment Fund and the Yellow River Delta Development Guarantee Company. These entities offer financial support to enterprises developing agricultural technologies.

The second is talent cultivation. From 2010 to 2012, Shandong Province has allocated 5 million yuan annually to specifically support the recruitment and training of urgently needed talents in the Yellow River Delta region.

The third is technology development. The Yellow River Delta High-tech Agricultural Industry Demonstration Zone has been established to specifically explore the comprehensive use of salt-alkaline land. To date, 147 technologies for the use of saline and alkaline soils have been developed, and 55 new varieties (or strains) of salt-tolerant crops have been cultivated. For example, the newly bred peanut variety "Huayu 9307" has drought resistance, flood tolerance, and salinity tolerance. It achieves a yield of 625.9 kg/ha in salt-alkaline soils.

Fourth, one million acres of wasteland and one million acres of low-yield farmland have been transformed into high-standard farmland, with the total investment exceeding 20 million US dollars. These measures have enhanced the overall productivity of agriculture.

Table 2 Baseline results. TFP stands for agricultural total factor productivity. And du is the city group variable, dt is the time group variable. $^{***}/^{**}/^{*}$ represent the significance at the 1%, 5%, and 10% levels. The coefficient and significance level of the policy term indicate the ecological economic zone effectively improved agricultural total factor productivity

Variables	(1)	(2)
	TFP	TFP
du	-0.415***	-0.537***
	(-5.48)	(-5.38)
dt	0.218***	0.453
	(3.03)	(1.27)
policy	0.387***	0.404***
	(6.93)	(7.19)
Constant	2.015***	2.364***
	(34.07)	(5.59)
Control variables	Yes	Yes
Time fixed affects	Yes	Yes
City fixed effects	Yes	Yes
Observations	288	288
R^2	0.520	0.528

Heterogeneity analysis

We also analyzed the heterogeneity of policy effects. We examine the impact of the policy on the yield per acre of grain crops. The results of column (1) in Table 3 show that the policy increased the yield per acre of grain crops by 1.8%. These results are related to the expansion of high-standard farmland and the cultivation of salt-tolerant crops. The expansion of high-standard farmland has increased land productivity. The expansion of salt-tolerant crops has increased overall production levels.

The interaction term of policy and the share of primary industry is introduced in column (2) of Table 3. The interaction term of policy and the natural logarithm of farmers' disposable income is also introduced in column (3). Both coefficients of the interaction terms are positive at the 1% level, which implies that in regions with higher agricultural GDP and farmers' net income, the policy results in a significant increase in agricultural total factor productivity. In reality, a region with a high share of agriculture, indicating a larger scale of agricultural production, benefits from the diffusion and application of new technologies, making the policy impact more significant. Higher per capita disposable income implies that farmers are wealthier and can increase capital and technological investment in agricultural production. Therefore, we anticipate a gradual improvement in agricultural productivity within the zone.

By introducing the interaction terms between the policy and years, we examined the dynamic effects of the policy over time. The results in column (4) of Table 3 demonstrate that the policy's positive impact gradually decreases year by year. This reflects the law of diminishing marginal returns, which may be related to insufficient follow-up support measures in the zone. The most positive effect was observed in 2010.

Mechanism analysis

This study analyzes the mechanism of the policy effect from two perspectives: agricultural research and development (R&D) and technological substitution.

We measure agricultural technology research and development by the proportion of agricultural R&D funds in fiscal expenditures. The results in column (1) of Table 4 indicate that government spending on agricultural R&D increased by 0.5% after the establishment of the zone. The coefficient of the policy in column (2) is also significant, and the coefficient of the proportion of agricultural R&D funding is positive and significant at the 5% level. This can be interpreted as the policy increasing agricultural productivity through

Table 3 Heterogeneity analysis and dynamic impact. Agct is the natural logarithm of the yield per acre of grain crops. TFP stands for agricultural total factor productivity. And du is the city group variable, dt is the time group variable; policy equals du×dt; policy2010–policy2020 represents the time dummy variables for year 2010–2020. Agricultural share represents the proportion of agriculture, and High income indicates the level of farmers' income. ***/**/* represent the significance at the 1%, 5%, and 10% levels

Variables	(1) Agct	(2) TFP	(3) TFP	(4) TFP
du	-0.465***	-0.453***	-0.592***	-0.232**
	(-3.18)	(-4.51)	(-5.94)	(-2.50)
dt	0.037	0.562	0.279	0.526
	(0.13)	(1.55)	(0.80)	(1.41)
policy	0.018**			
	(2.23)			
Agricultural share		0.704***		
		(2.75)		
High income			0.602***	
			(5.44)	
policy2010				0.388***
				(3.71)
policy2011				0.372***
				(2.70)
policy2012				0.316**
				(2.21)
policy2013				0.185**
				(2.03)
policy2014				0.134**
				(2.00)
policy2015				0.018**
				(1.99)
policy2016				0.010*
				(1.93)
policy2017				0.017*
				(1.86)
policy2018				0.069
				(0.72)
policy2019				0.048
				(0.53)
policy2020				0.051
				(0.59)
Constant	6.717***	2.421***	2.293***	2.131***
	(17.06)	(5.63)	(5.84)	(4.56)
Control variables	Yes	Yes	Yes	Yes
Time fixed affects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Observations	288	288	288	288
R^2	0.785	0.538	0.577	0.439

Table 4 Mechanism analysis results. TFP stands for agricultural total factor productivity. And du is the city group variable, dt is the time group variable; policy equals du×dt; ratio_keji stands for agricultural R&D; diesel is mechanization; pesticides refer to the amount of pesticide usage. ***/**/* represent the significance at the 1%, 5%, and 10% levels

Variables	(1) ratio_keji	(2) TFP	(3) diesel	(4) TFP	(5) pesticides	(6) TFP
du	-0.019***	-0.441***	0.433***	-0.621***	-0.914***	-0.619***
	(-6.72)	(-3.82)	(3.81)	(-5.86)	(-7.53)	(-5.55)
dt	0.034***	0.277	2.224***	0.020	2.315***	0.659
	(4.98)	(0.73)	(9.35)	(0.05)	(8.78)	(1.60)
policy	0.005***	0.377***	0.259***	0.353***	-0.054**	0.408***
	(3.25)	(6.38)	(5.83)	-0.621***	(2.04)	(7.34)
ratio_keji		5.157**				
		(2.05)				
diesel				0.195***		
				(2.70)		
pesticides						-0.089**
						(-2.18)
Constant	0.054***	2.086***	-4.564***	3.252***		2.251***
	(6.06)	(4.60)	(-16.01)	(6.37)		(5.32)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed affects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288	288	288	288	288	288
R^2	0.661	0.535	0.968	0.537	0.953	0.529

increased spending on agricultural R&D. This result suggests that the government has made significant investments in agricultural technology and the breeding of salt-tolerant crops.

Considering that some agricultural machinery may remain unused, we assess the level of mechanization by using the natural logarithm of diesel fuel consumption per $10,000 of agricultural output. Comparing the results in columns (3) and (4) of Table 4, we find that the policy promotes agricultural total factor productivity through increased mechanization. This result is understandable, because the gradual adoption of new agricultural machinery has enhanced agricultural total factor productivity.

Developing ecological agriculture requires the extensive use of eco-farming techniques. In general, the use of organic techniques tends to reduce the use of fertilizers and pesticides. Due to the difficulties in directly measuring the use of ecological techniques, we indirectly measure the use of ecological techniques by examining the consumption of fertilizers and pesticides per $10,000 of agricultural output.

We first investigated whether the policy enhanced production efficiency by reducing the use of chemical fertilizers. However, the results were not significant, which rules out the possibility of chemical fertilizer usage as a potential pathway. Therefore, we did not include this result in the table.

Similarly, we examined if pesticide usage served as a pathway. Results in columns (5) and (6) of Table 4 demonstrate that the policy enhanced agricultural total factor productivity by reducing pesticide usage.

Robust test

The growth rate of total agricultural output value was also used as the dependent variable. In Table 5, the result of column (1) shows that the policy improved the growth rate by 21.4%. Moreover, excluding Weifang and Yantai from the treatment group may lead to sample selection issues. Therefore, we re-analyzed by including these two cities in the treatment group. As shown in column (2) of Table 5, the coefficient of the policy is 0.315, significant at the 1% level, and the conclusion remains unchanged.

Discussion

Our study is consistent with the studies of Wang et al. (2018), Lant et al. (2005), and Nguyen et al. (2023) in focusing on the effects of regional environmental economic policies. However, Wang et al. (2018) specifically analyzed the impact of land environmental management policies on the area of ecological farmland. They did not investigate whether changes in the area of ecological agricultural land would affect the level of agricultural production. Lant et al. (2005) examined the effect of agricultural ecosystem management policies on the agricultural environment, specifically soil erosion, farm income, and water quality. However, in discussing farm income, they only described the temporal trends of income changes without explaining the underlying reasons for these changes. Nguyen et al. (2023) focused on

Table 5 Robust test. TFP stands for agricultural total factor productivity. ZLV is the growth rate of total agricultural output value. And du is the city group variable, dt is the time group variable, policy equals du×dt; du1 means that Weifang and Yantai are classified as part of the treatment group. ***/**/* represent the significance at the 1%, 5%, and 10% levels

Variables	(1) ZLV	(2) TFP
du	0.017	
	(0.48)	
dt	0.047*	0.332
	(1.93)	(0.91)
policy	0.214**	
	(2.17)	
du1		-0.438***
		(-4.34)
du1×dt		0.315***
		(5.15)
Constant	0.143	2.173***
	(0.94)	(5.07)
Control variables	Yes	Yes
Time fixed effects	Yes	Yes
City fixed effects	Yes	Yes
Observations	272	288
R^2	0.457	0.507

the impact of Thailand's Eastern Economic Corridor policy on economic growth and the ecological environment. While their research included crop cultivation, it analyzed the policy's effect on the structure of crop cultivation without examining its effect on agricultural total factor productivity.

Unlike the above studies, our research extends the impact of regional environmental economic policies from land use and environmental changes to the agricultural production sector. Uniquely, we quantified the impact of the Yellow River Delta High Efficiency Ecological Economic Zone policy on agricultural total factor productivity. We found that the policy led to a significant 40% increase in agricultural total factor productivity, especially in areas with a high share of agriculture and high per capita disposable income. However, we also found that this positive effect has been declining annually since 2010.

Moreover, our study also enriches the research on the use of saline-alkaline land. Chen et al. (2022) emphasized the need for biotechnological measures to improve saline-alkali soils. Devkota et al. (2022) advocated the use of water-saving irrigation techniques and proper nitrogen fertilizer application to maintain nutrients in saline-alkali soils, and focused on cotton and wheat cultivation to increase yields, with their research targeting the saline-alkali soils of southern Uzbekistan. In addition, our study finds that increased investment in agricultural R&D to develop new technologies and crop varieties suitable for planting in saline-alkali soils can also increase the productivity of these lands.

However, this study is not without its limitations. Since 2010, the positive effect of the policy has declined, which may be related to a slowdown in technological progress. In the early stages, the government could increase investment in agricultural technology R&D, thereby increasing the efficiency of agricultural production. Over time, the pace of technological innovation may slow, limiting the pace of agricultural development. Of course, this hypothesis needs to be tested. In addition, our analysis is limited to prefecture-level urban data, which may not capture the full heterogeneity and micro-level dynamics of different types of farms and agricultural production within ecological economic zone.

Future research should address these limitations by incorporating more detailed data, including farm-level analyses, which could provide deeper insights into the effectiveness of specific agricultural technologies and management practices. In addition, studying the socio-economic impacts of increases in agricultural total factor productivity, such as income distribution among farmers, will provide a more comprehensive understanding of policy implications. The research design of this paper can be extended to other areas facing similar ecological challenges, providing valuable lessons for global sustainable agricultural development.

Conclusion and recommendations

This paper analyzes the impact of ecological economic zone policy on agricultural production efficiency. The results show that the policy increased agricultural total factor productivity by 40%, and the heterogeneity analysis shows that this positive effect is particularly pronounced in regions with a high proportion of agriculture and high per capita disposable income of farmers. However, this positive effect has diminished year by year since 2010. Mechanism tests suggest that the increase in agricultural R&D, the improvement in mechanization, and the application of ecological technologies have boosted agricultural total factor productivity. The results highlight the need for additional measures to maintain the positive effects in the long run. The following policy implications can be considered.

First, strengthen innovation and promotion of agricultural science and technology. Increase investment in agricultural research, especially in areas such as the development of adaptive and stress-resistant crop varieties, smart farming technologies, and biotechnology. Establish agricultural science and technology innovation platforms to facilitate the rapid transformation and application of research results, thereby improving agricultural productivity and sustainability.

Second, promote the development of organic and precision agriculture. Promote the adoption of ecological farming practices, such as crop rotation, organic farming, and biodiversity conservation, to reduce dependence on chemical fertilizers and pesticides. Utilize modern information technology, such as big data, the Internet of Things and artificial intelligence, to achieve precise fertilization, irrigation, and pest control, thereby increasing the efficiency of resource use.

Third, implement differentiated support policies. Formulate and implement differentiated support policies according to the different levels of agricultural development and ecological conditions in different regions. Focus on supporting areas with fragile ecological environment and poor agricultural production conditions, and provide customized technical and financial support to improve agricultural production capacity.

Declarations

Conflict of interest The authors declare no competing interests.

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