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Can Farmland Transfer Reduce Fertilizer Nonpoint Source Pollution? Evidence from China

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Abstract: China repeatedly surpasses international fertilizer safety limits, resulting in significant fertilizer nonpoint source pollution (denoted as FNSP), which adversely affects food security and agricultural sustainability. Simultaneously, farmland transfer has emerged as a pivotal strategy for transitioning between agricultural production methods. The present study aims to investigate the relationship between farmland transfer and FNSP. In line with the aim of the study, based on China's panel data from 2005 to 2020, the fixed-effect model, mediating-effect model, spatial Durbin model, and threshold regression model are employed. The findings reveal that farmland transfer exerts a significant inhibitory effect on FNSP. The reduction in FNSP through farmland transfer is facilitated by the decrease in fertilizer application intensity and increase in compound fertilizer application. Further, farmland transfer demonstrates a significant spatial spillover effect on FNSP, mitigating pollution levels within regions and influencing neighboring areas. Moreover, a nonlinear relationship between farmland transfer and FNSP is observed. These findings contribute to understanding the intricate dynamics between agricultural land management strategies and environmental sustainability, offering valuable insights for policymakers and stakeholders engaged in promoting green and sustainable agricultural practices.

Keywords: farmland transfer; fertilizer nonpoint source pollution; environmental benefits; sustainable farmland utilization; sustainable agricultural development

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1. Introduction

Fertilizer stands as a crucial agricultural production factor [1], with its contribution to food growth previously reaching 56.81% [2], thereby playing an indispensable role in ensuring food security in China [3]. Historically, China's agricultural development has heavily relied on chemical fertilizer inputs [4]. China not only ranks as the world's largest fertilizer producer but also as a substantial user of fertilizer [5]. According to data from the National Bureau of Statistics, China's total fertilizer application reached 50.79 million tons in 2022, with a fertilizer application intensity of 278.79 kg/ha, exceeding the internationally recognized safety standard of 225 kg/ha by 1.24 times [6]. However, the effective utilization efficiency remains less than half that of developed countries [7]. Notably, fertilizer's marginal contribution rate is gradually declining [8]. Excessive fertilizer inputs not only escalate the economic costs of agricultural production [9] but also lead to severe fertilizer nonpoint source pollution (denoted as FNSP) [10,11], posing significant threats to food security and the sustainable development of agriculture [12–14]. Recognizing the gravity of fertilizer pollution, the Chinese government has issued policy documents such as the "Action Plan for Zero Growth of Fertilizer Use by 2020" to guide the reduction in fertilizer application. Additionally, Central Document No. 1 of 2021 and 2022 emphasizes the urgent need for deep implementation of fertilizer reduction and efficiency measures. Hence, further exploration to reduce FNSP remains a vital issue that warrants continuous discussion for the sustainable development of agriculture in China [15].

Indeed, allocating production factors such as fertilizers inherently reflects natural resource endowments like arable land. This suggests an intrinsic connection between fertilizer application and the utilization of arable land [16,17]. Farmland transfer entails the redistribution of land resources through various means such as transfer-outs, subcontracting, swaps, and cooperation, wherein farmers or agricultural organizations transfer their land contract rights and usage rights wholly or partially [18–21]. It serves as a significant mechanism for reconfiguring land resources. Farmland transfer emerges as an effective strategy for mitigating the fragmentation of arable land, altering planting structures, and fostering agricultural modernization [22–24]. Policies such as the "three rights of ownership" have fostered the standardized development of China's farmland transfer market and facilitated the expansion of moderate-scale agricultural operations [25,26]. However, despite these advancements, the persistent trend of excessive chemical fertilizer usage persists. Within academia, a unified conclusion regarding this matter has yet to be reached, forming two distinct viewpoints.

One perspective contends that farmland transfer and large-scale agricultural operations facilitate fertilizer reduction [27–31]. Scale growers typically employ more judicious fertilizer than small farmers [32]. Farmland transfer enables the realization of economies of scale, thereby expanding avenues for knowledge and technology transfer among farmers. Moreover, it enhances farmers' comprehension and utilization of cleaner production methods, subsequently refining factor input management and fostering more scientific and rational fertilizer application practices [27,33–35]. Another perspective suggests that farmland transfer and large-scale operations do not necessarily lead to fertilizer reduction. The farmland transfer may introduce management rights instability [36], potentially fostering moral hazard among farmers who may prioritize short-term gains and invest heavily in fertilizers [37,38]. Furthermore, expanding the operational scale may increase the demand for production factors and incentivize labor substitution with inputs such as fertilizers, thereby increasing chemical fertilizer usage [39,40]. Studies have analyzed the connection between farmland transfer and fertilizer usage. However, there is a relative scarcity of research directly investigating the correlation between farmland transfer and FNSP. Moreover, the exploration of its underlying mechanisms remains somewhat limited. Furthermore, given the spatial delineation of farmland across various regions, it becomes essential to analyze the environmental ramifications of farmland transfer from a spatial perspective.

This paper contributes to three main aspects. Firstly, this research advances research content by integrating farmland transfer and FNSP within a unified analytical framework. While existing studies have focused on the relationship between agricultural land transfer and fertilizer application, this paper explores the impact of farmland transfer on FNSP. Employing methods such as the fixed-effect model and mediating-effect model, this paper comprehensively analyzes this relationship and its underlying mechanisms. Secondly, this paper broadens research perspectives by employing more representative provincial macro panel data for empirical analysis. Unlike studies relying on micro research data from specific regions, this approach aims to enhance the generalizability of findings to the entire nation. By analyzing heterogeneity, the paper endeavors to provide insights applicable on a broader scale. Lastly, the paper extends research by exploring the nonlinear relationship between farmland transfer and FNSP. This exploration contributes to enriching related research by shedding light on nuanced dynamics that were previously underexplored.

The remainder of this paper is structured as follows. Section 2 provides a theoretical analysis and formulates the research hypothesis. Section 3 describes the research methodology and data sources. Section 4 presents and analyzes the main research findings. Section 5 provides further discussion. Section 6 summarizes the main conclusions.

2. Theoretical Analyses

Schultz noted that transitioning traditional agriculture necessitates the incorporation of modern factors of production [41]. The core of reducing FNSP lies in altering traditional production methods and enhancing the ecological environment, thereby generating significant positive externalities. Rational economic actors, such as farmers, prioritize their economic gains and are unlikely to voluntarily enhance the environment at the expense of their own interests without external constraints [42]. The prevalence of small-scale farming characterizes agricultural production in China, as highlighted by the theory of induced technological change, where the utilization of fertilizers and other production factors can enhance land output within resource constraints [43,44]. Nonetheless, the fragmented and dispersed nature of land ownership makes it challenging to establish a unified field management model, leading to widespread instances of excessive fertilization [4]. With the progression of farmland transfer, substantial portions of fragmented agricultural land have consolidated into the hands of large-scale agricultural entities, such as large-scale farming households and cooperatives, enabling the optimization and restructuring of agricultural land resource allocation [45]. On the one hand, adhering to economies of scale principles, large-scale farming operations can curtail marginal production costs, consequently reducing the application of pesticides, fertilizers, and other sources of surface pollution per unit area of agricultural land [46]. As operational land scale expands, agricultural specialization deepens, prompting increased adoption of agricultural machinery and equipment due to limited labor supply elasticity [47]. Specialized agricultural machinery facilitates deep plowing and loosening, enhancing fertilizer utilization efficiency and reducing pollution generation [48]. Conversely, large-scale operators typically possess superior agricultural knowledge and management skills [9]. Expert farmers can accurately discern the deleterious effects of irrational fertilizer inputs, promptly adjust fertilizer types and structures, optimize micronutrient proportions, decrease nitrogen and phosphorus fertilizer usage, and prioritize compound fertilizer application. Thus, this paper posits the following research hypotheses:

Hypothesis 1: *Farmland transfer can significantly reduce FNSP.*

Hypothesis 2: *Farmland transfer can mitigate FNSP through two pathways: by reducing fertilizer application intensity and by promoting compound fertilizer application.*

Spatial econometrics incorporates spatial factors and unveils the spatial correlation of economic characteristics or natural attributes across regions [49]. From a spatial perspective, neighboring regions often share similar resource endowments, cultivation structures, production methods, and geomorphological features, fostering spatial interaction in FNSP between these regions [50]. Moreover, contiguous farmland land borders between neighboring regions can trigger environmental effects of farmland transfer, generating spillovers. The inhibitory effect of farmland transfer on FNSP can produce spatial overflow through two main pathways. Firstly, positive outcomes from farmland transfer implementation in one region can serve as a demonstration effect for neighboring regions, prompting them to emulate the experience and foster farmland transfer development, thereby reducing FNSP in these regions. Secondly, competition among local governments in China may incentivize regions that improve their environment through farmland transfer to receive policy support from higher-level governments, granting them a relative advantage in regional competition. This competitive mechanism motivates other regions to emulate these practices and vigorously develop farmland transfer to achieve environmental benefits. Consequently, this paper posits the following research hypothesis:

Hypothesis 3: *Farmland transfer has a spatial spillover effect on the suppression of FNSP.*

Based on the above analysis, this paper constructs the following empirical analysis framework (Figure 1).

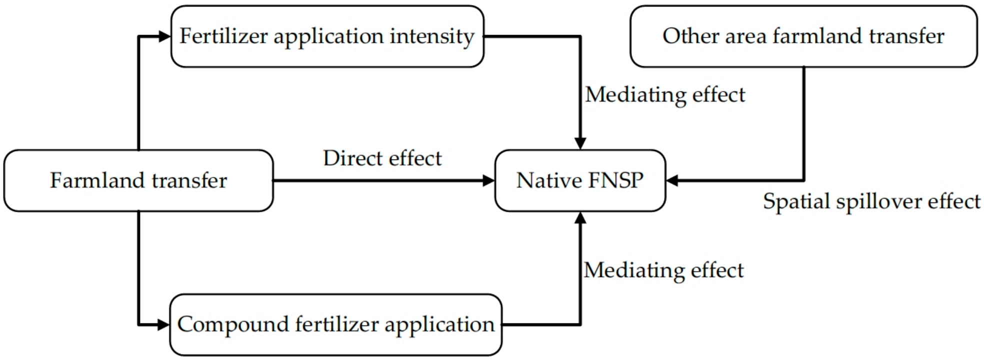

Figure 1. Main framework of the empirical study.

3. Materials and Methods

3.1. Research Methodology

3.1.1. Measurement of FNSP

Existing statistics still need to directly quantify the FNSP emissions accurately and scientifically. This study measured FNSP using the unit survey method and inventory analysis method, supplemented by the loss coefficient method [51,52]. Nitrogen, phosphorus, and compound fertilizers were considered sources of FNSP pollution [53]. Fertilizers primarily contribute to water pollution through surface runoff, farmland drainage, and underground leaching [54,55]. As a result, pollutant indicators including total nitrogen (TN), nitrate nitrogen (NO_3^-), ammonia nitrogen (NH_4^+), total phosphorus (TP), and dissolved total phosphorus (DTP) were employed [56]. The calculation formula is given by:

$$FNSP = \sum FNSP_{ij} = \sum (T_i \times \rho_{ij} \times \eta_{ij}) \quad (1)$$

where $FNSP_{ij}$ represents the amount of pollutant j produced by pollution unit i. Specifically, ρ_{ij} denotes the pollution production coefficient. T_i denotes the amount of fertilizer application refraction [57], with total nitrogen refraction coefficients of 1, 0, and 0.33 for nitrogen fertilizer, phosphorus fertilizer, and compound fertilizer, respectively, and total phosphorus refraction coefficients of 1, 0.44, and 0.15 for the same fertilizers, respectively [58]. η_{ij} represents the loss coefficient. The loss coefficients for each region are provided in Table 1 [59].

Table 1. The loss coefficients for each region.

Region	Loss Coefficient η (%)				
	TN	**NO_3^-**	**NH_4^+**	**TP**	**DTP**
Beijing, Tianjin, Shandong, Hebei, Henan	1.173	0.489	0.122	0.199	0.054
Shanxi, Shaanxi, Ningxia	0.293	0.050	0.041	0.215	0.039
Heilongjiang, Jilin, Liaoning	0.422	0.133	0.054	0.096	0.012
Inner Mongolia, Gansu, Xinjiang, Qinghai	0.511	0.184	0.025	0.108	0.000
Hunan, Hubei, Zhejiang, Shanghai, Anhui, Jiangsu	1.536	0.867	0.147	0.410	0.147
Yunnan, Guangxi, Fujian, Jiangxi, Guangdong, Chongqing, Sichuan, Guizhou, Hainan	0.868	0.239	0.149	0.497	0.086

3.1.2. Fixed Effects Model

To prevent the omission of explanatory variables and to account for both individual and time effects, this paper established a two-way fixed-effect model for estimation [60]:

$$FNSP_{ij} = \alpha_0 + \alpha_1 Transfer_{it} + \alpha_2 Control_{it} + \theta_t + \mu_i + \varepsilon_{it} \quad (2)$$

where $FNSP_{it}$ and $Transfer_{it}$ denote FNSP and farmland transfer for region i in period t. θ_t, μ_i, and ε_{it} represent time-fixed effects, individual-fixed effects, and random errors, respectively.

3.1.3. Mediating-Effect Model

To analyze the pathway through which farmland transfer inhibits FNSP, this paper established a mediating-effect model in the form of [61,62]:

$$\begin{gathered} FNSP_{ij} = \alpha_0 + \alpha_1 Transfer_{it} + \alpha_2 Control_{it} + \theta_t + \mu_i + \varepsilon_{it} \\ (Mediating_{it}) = \beta_0 + \beta_1 Transfer_{it} + \beta_2 Transfer_{it} + \theta_t + \mu_i + \varepsilon_{it} \\ FNSP_{ij} = \delta_0 + \delta_1 Transfer_{it} + \delta_2 (Mediating_{it}) + \delta_3 Control_{it} + \theta_t + \mu_i + \varepsilon_{it} \end{gathered} \tag{3}$$

where $Mediating_{it}$ represents the mediating variables.

3.1.4. Global Moran's I Index

This study uses the global *Moran's I* index to analyze the global spatial evolution characteristics of farmland transfer and FNSP [63]. The index is calculated as follows [49]:

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{i=1}^{n} W_{ij}(x_i - \overline{x})^2} \tag{4}$$

where n is the sample size and Wij is the spatial weight matrix; to ensure the robustness of the estimation results, the following three matrices are selected in this paper, respectively:

$$W_1 = \begin{cases} 1 \cdots\cdots i \text{ is adjacent to } j \\ 0 \cdots\cdots i \text{ is not adjacent to } j \end{cases} \tag{5}$$

$$W_2 = \begin{cases} \frac{1}{d} \cdots\cdots i = j \\ 0 \cdots\cdots i \neq j \end{cases} \tag{6}$$

$$W_3 = \begin{cases} \frac{1}{d^2} \cdots\cdots i = j \\ 0 \cdots\cdots i \neq j \end{cases} \tag{7}$$

where d denotes the Euclidean distance between region i and region j calculated based on latitude and longitude.

3.1.5. Spatial Durbin Model

The spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM) are commonly employed methods for analyzing spatial effects, with the ability to transform them into each other under certain conditions [64]. In this paper, an SDM is constructed, and a series of tests are conducted to assess its appropriateness. The model is defined as follows [65]

:

$$FNSP_{it} = \rho\sum_{j=1}^{n} W_{ij} FNSP_{it} + \alpha Transfer_{it} + \beta\sum_{j=1}^{n} W_{ij} Transfer_{ij} + \omega X_{jt} + \tau\sum_{j=1}^{n} W_{ij} X_{jt} + \theta_t + \mu_i + \varepsilon_{it} \tag{8}$$

When $\beta = 0$, the SDM simplifies to the SAR, and when $\beta + \alpha\rho = 0$, it simplifies to SEM [66]. Relying on point estimates from traditional spatial regression models to estimate spatial spillover effects may yield misleading conclusions. Therefore, this study utilizes partial differential estimation to assess the direct, indirect, and overall impacts of farmland transfer on FNSP:

$$\left[\frac{\partial FNSP_1}{\partial Transfer_1} \cdots \frac{\partial FNSP_n}{\partial Transfer_2}\right] = \begin{bmatrix} \frac{\partial FNSP_1}{\partial Transfer_{11}} & \cdots & \frac{\partial FNSP_n}{\partial Transfer_{1n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial FNSP_1}{\partial Transfer_{n1}} & \cdots & \frac{\partial FNSP_n}{\partial Transfer_{nn}} \end{bmatrix} = (I - \rho W)^{-1}(\alpha I + \beta W) \tag{9}$$

The mean of the diagonal sum represents the direct effect, the non-diagonal sum signifies the indirect effect, and the sum of these two components yields the total effect [67–69].

3.1.6. Threshold Effect Specification

Drawing on Hansen's research, this study employs a panel data threshold regression model to investigate the nonlinear effect of farmland transfer on FNSP. The calculation is performed as [70]:

$$FNSP_{it} = \alpha_0 + \alpha_1 Control + \beta_1 Transfer \cdot D(Transfer < \theta_1) + \beta_2 Transfer \cdot D(\theta_1 < Transfer < \theta_2) + \cdots\cdots + \beta_n Transfer \cdot D(Transfer > \theta_{n-1}) + \mu_{it} \quad (10)$$

where θ_1, θ_2,. . ., θ_n denote the threshold values, $D(\cdot)$ represents the indicator function, and μ_{it} stands for the random disturbance term.

3.2. Variable Selection

The FNSP calculated in the previous section is chosen as the explanatory variable in this paper, denoted as *FNSP*.

The core explanatory variable selected in this paper is farmland transfer (*Transfer*), expressed as the ratio of the area of cultivated land transferred under a family contract to the total cultivated land area under a family contract [71,72].

The control variables selected in this paper are as follows. Educational level (*Education*) is expressed as the average schooling years of the rural population and is calculated by the formula: $(no + primary \times 6 + junior \times 9 + senior \times 12 + college \times 15)/all$ where *no* represents the number of people who have not attended school, *primary*, *junior*, *senior*, *college* represents the number of people in elementary school, middle school, high school, college, and above, respectively, and *all* represents the number of people who are six years old and above. Agriculture disaster (*Disaster*) is measured by the ratio of the affected agricultural area to the total cultivated area of crops. Agricultural Support (*Support*) represents the expenditure on agriculture, forestry, and water affairs. The degree of agricultural mechanization (*Machine*) is expressed in terms of the total power of agricultural machinery. The effective irrigated area indicates irrigation (*Irrigation*). Agricultural structure (*Structure*) represents the proportion of agricultural output value in the overall output value of agriculture, forestry, animal husbandry, and fishery.

As for the mechanism variables, this paper selects fertilizer application intensity (*Intensity*) and compound fertilizer application (*Compound*) as the mediating variables, respectively [27,73]. Specifically, fertilizer application intensity is characterized by the amount of fertilizer applied per unit of sown area, calculated as the discounted amount of fertilizer applied divided by the total sown area of the crop. The compound fertilizer application is characterized by the proportion of compound fertilizer in the fertilizer, calculated as the pure amount of compound fertilizer applied divided by the pure amount of chemical fertilizer applied.

3.3. Data Sources

This paper selects 30 provinces in mainland China, excluding Hong Kong, Macao, Taiwan, and the Tibet Autonomous Region, as the study sample from 2005 to 2020. The data necessary for calculating FNSP were sourced from the China Rural Statistical Yearbook. Information regarding farmland was obtained from the China Rural Management Statistical Yearbook, wherein explicit records of the total area of cultivated land transferred under family contracts and the area of cultivated land operated under family contracts were provided. The ratio of these two figures was utilized to characterize farmland transfer. Population data were extracted from the China Demographic Statistics Yearbook, while education-related statistics were sourced from the China Education Statistical Yearbook. Additional data were gathered from the China Rural Statistical Yearbook. It is important to note that all data utilized in this study represent actual values for the respective years. Missing values in each variable are filled in using linear interpolation. Natural logarithms are applied to all variables in the empirical analyses to mitigate differences in data magnitude. The descriptive statistics for each variable are presented in Table 2.

Table 2. Descriptive statistics of variables.

Variable	Unit	Mean	Std. Error	Min	Max
Explained variable					
FNSP	10,000 Ton	4.389	1.278	0.786	6.435
Core explanatory variable					
Transfer	%	0.203	0.139	0.013	0.648
Control variables					
Education	Year	2.017	0.092	1.637	2.268
Disaster	%	0.334	0.502	0.000	3.114
Support	10,000 CNY	6.917	0.460	5.368	12.963
Machine	10,000 KW	7.592	1.091	4.543	9.499
Irrigation	1000 Hectare	7.247	1.020	4.694	8.729
Structure	%	0.504	0.083	0.304	0.678
Mediating variables					
Intensity	Ton/1000 Hectare	5.820	0.368	4.567	6.684
Compound	%	0.292	0.072	0.132	0.528

4. Results

4.1. Characteristics of Farmland and Transfer and FNSP Reality

Taking 2005, 2010, 2015, and 2020 as benchmark years, each province's farmland transfer intensity is categorized by the natural breakpoint method of ArcMap 10.8 software into five levels: low, medium-low, medium, medium-high, and high. Figure 2 illustrates the spatial and temporal evolution characteristics of farmland transfer. Broadly, the high-intensity farmland transfer areas gradually expand from the southeast coast to the northeast. In 2005, only Guangdong and Zhejiang provinces were classified as high-intensity areas; by 2020, Beijing, Jiangsu, Shanghai, and Heilongjiang had also joined this category. Conversely, the intensity of farmland transfer in southwestern regions such as Sichuan, Chongqing, Guizhou, Yunnan, and Guangxi appear relatively subdued. The degree of farmland transfer in central and western regions demonstrates a pattern of initial weakening followed by resurgence.

Likewise, the FNSP of each province is segmented, and the outcomes are depicted in Figure 3. At the national level, there is a discernible trend of overall improvement in FNSP, with each province's FNSP characterized by spatial agglomeration. From 2005–2015, high-intensity FNSP regions were primarily concentrated in Hebei, Shandong, Henan, Jiangsu, Anhui, Hubei, Hunan, and others, displaying a clear spatial agglomeration pattern. Medium-high-intensity zones gradually shifted from western regions like Sichuan and Guangdong and southern regions towards central and northern areas. Conversely, the northeastern region exhibited a trend of initial strengthening followed by weakening. Medium-intensity zones transitioned from north to south, while medium-low-intensity areas predominantly clustered in central regions such as Shaanxi. Low-intensity areas were mainly concentrated in northwestern regions like Gansu and Qinghai.

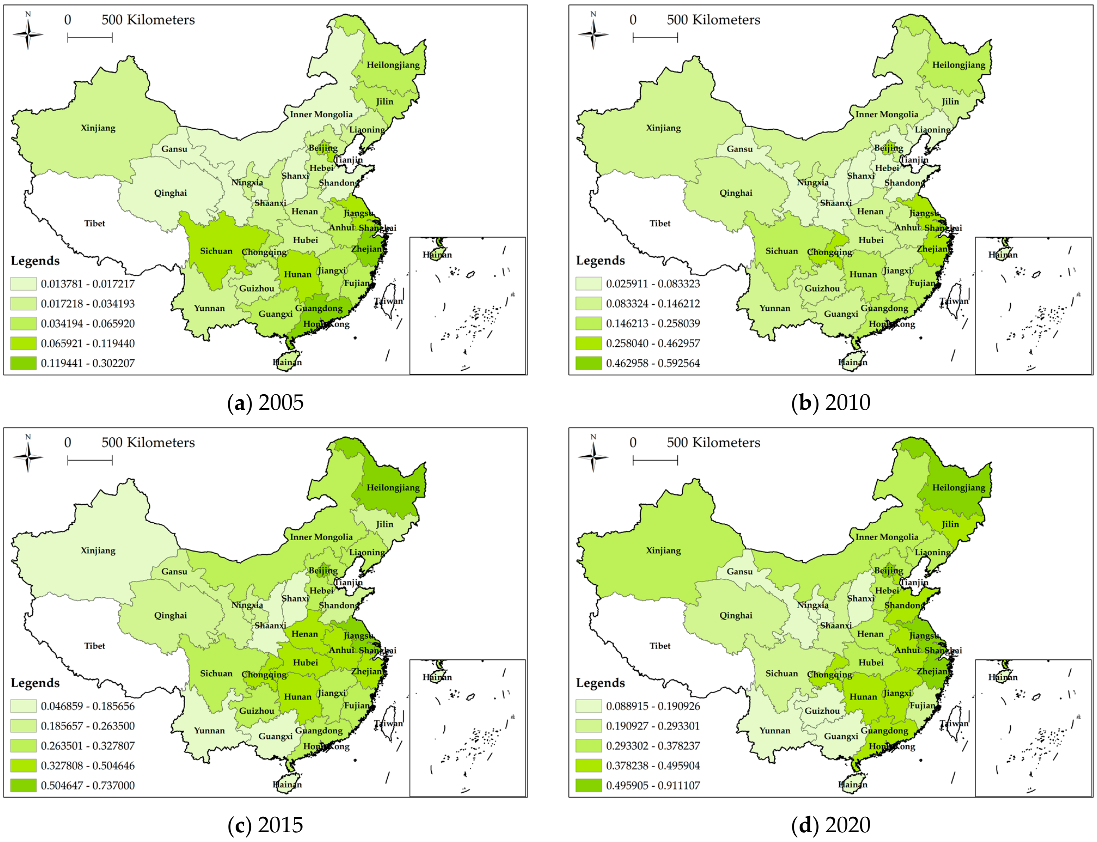

Figure 2. Temporal evolution trend of farmland transfer.

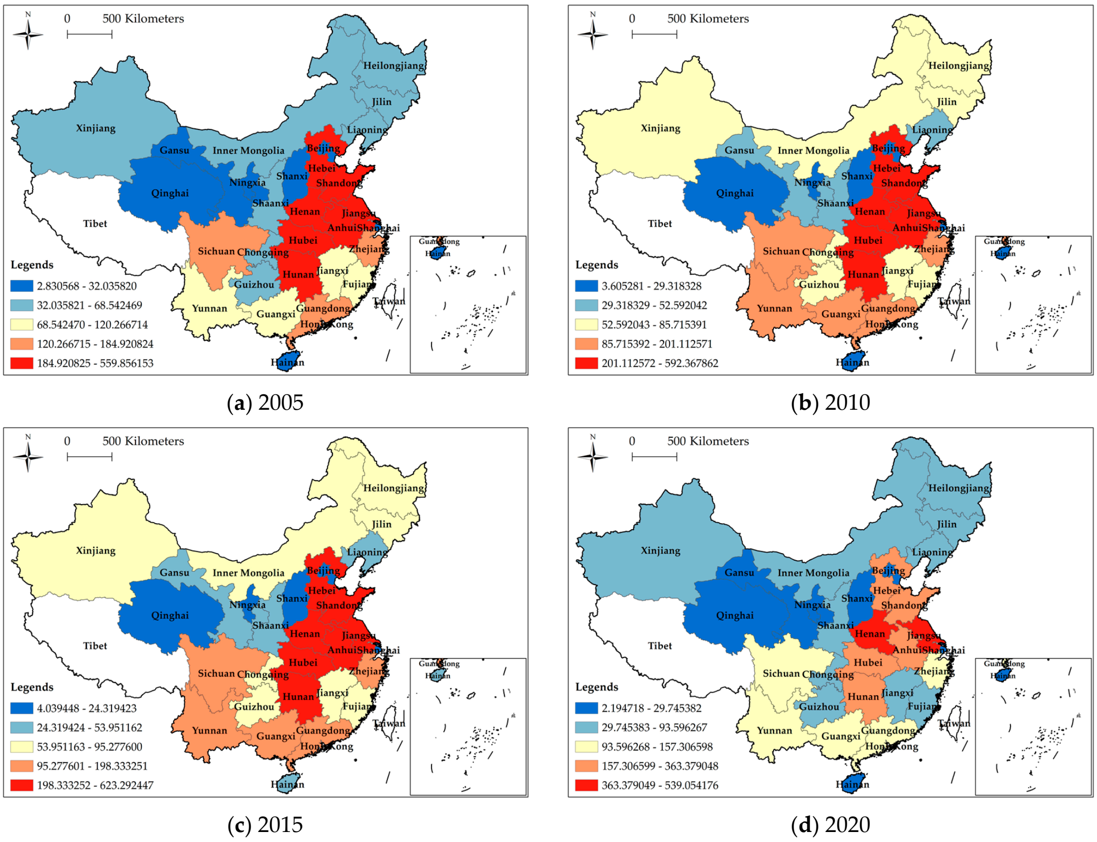

Figure 3. Temporal evolution trend of FNSP.

4.2. Baseline Regression Results for the Impact of Farmland Transfer on FNSP

This paper employs the stepwise regression method to examine the impact of farmland transfer on FNSP, with the results presented in Table 3. In model (1), the regression coefficient of farmland transfer is −0.781, passing the 1% level test without including any control variables, suggesting a reduction in FNSP with farmland transfer development. Model (2), model (3), and model (4) progressively incorporate control variables with consistently negative regression coefficients for farmland transfer, and the model fit is improved and the estimation results are robust. Therefore, hypothesis 1 is preliminarily supported.

Table 3. Baseline regression of the impact of farmland transfer on FNSP.

Variables	Model (1)	Model (2)	Model (3)	Model (4)
Transfer	−0.781 *** (0.133)	−0.798 *** (0.132)	−0.800 *** (0.131)	−0.418 *** (0.115)
Education		−0.592 ** (0.248)	−0.628 ** (0.246)	−0.646 *** (0.202)
Disaster		−0.065 *** (0.019)	−0.086 *** (0.021)	−0.069 *** (0.018)
Support			0.026 * (0.014)	0.008 (0.011)
Machine			0.016 *** (0.006)	0.011 ** (0.005)
Irrigation				0.650 *** (0.043)
Structure				−0.910 *** (0.240)
Constant	4.548 *** (0.028)	5.766 *** (0.504)	5.546 *** (0.504)	1.413 *** (0.543)
Individual fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
Observations	480	480	480	480
R^2	0.9919	0.9923	0.9925	0.9951

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

Among the control variables, educational level significantly negatively impacts FNSP. This is attributed to the higher environmental awareness among rural residents with increased education levels, leading to the adoption of more standardized fertilizer application practices, thus reducing FNSP. Agricultural disasters have a significant negative impact on FNSP. While these disasters affect agricultural production, they also prompt farmers to consider environmental factors, leading to changes in production methods and improvements in fertilizer usage. Agricultural structure significantly reduces FNSP. Higher proportions of agriculture are more susceptible to policy influence, and greater agricultural green development levels facilitate FNSP improvements. The regression coefficient of the agricultural mechanization degree on FNSP is significantly positive. Agricultural machinery facilitates the shift from labor-intensive to capital-intensive production, advances production technology, and increases inputs of modern factors like fertilizers, thus improving FNSP. The degree of irrigation is significantly positively correlated with FNSP at the 1% level, likely due to the prevalent use of irrigation methods such as diffuse irrigation, border irrigation, furrow irrigation, and flooding irrigation in China. These irrigation methods destroy the soil tillage layer and aggravate the loss of fertilizer nutrients and pollution.

4.3. Endogeneity Treatment and Robustness Test

The previous empirical analysis highlights the significant suppressive effect of farmland transfer on FNSP. However, it is important to note that as FNSP increases within a region, it can damage arable land quality and constrain farmland transfer development. Additionally, ecological damage caused by FNSP limits farmers' income potential and diminishes demand for farmland transfer to expand production. Consequently, the model may encounter endogeneity issues due to bidirectional causality.

Accordingly, this paper employs the lagged core explanatory and instrumental variables methods to address endogeneity [74]. Initially, the lagged one-period farmland transfer (*L1.Transfer*) serves as a proxy variable for regression. Subsequently, the farmland transfer with a two-period lag (*L2.Transfer*) is utilized as an instrumental variable to establish a two-stage least squares regression model (IV-2SLS). The instrumental variable is primarily selected due to the predevelopment of farmland transfer, which serves as a basis for subsequent development and meets relevance requirements [75]. The lagged two-period farmland transfer minimally influences the current FNSP, satisfying the exogenous criterion for instrumental variable selection.

In model (5) of Table 4, the coefficient of farmland transfer in the lagged one-period remains negative and statistically significant at the 1% level, validating the baseline regression results. In model (6), the results of the IV-2SLS method reveal a significant positive effect of the two-period lagged farmland transfer on the current period farmland transfer. In contrast, the suppressive effect on FNSP remains significant. The Anderson canonical correlation LM statistic passes the 1% level test, and the Cragg–Donald Wald F statistic exceeds the critical value of 16.380; the instrumental variable selection is appropriate [76]. In summary, the direction of the regression coefficients for farmland transfer does not change after addressing the endogeneity of the model, which is consistent with the baseline regression results.

Table 4. Results of endogeneity treatment.

Variables	Model (5)	Model (6): IV−2SLS	
	FNSP	*Transfer*	*FNSP*
L1.Transfer	−0.511 *** (0.114)		
L2.Transfer		0.487 *** (0.042)	−1.039 *** (0.244)
Constant	1.512 *** (0.558)	0.273 * (0.209)	1.423 ** (0.610)
Control variables	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Anderson canon. corr. LM statistic		139.391 ***	
Cragg–Donald Wald F statistic		184.293 > 16.380	
Observations	450	420	420
R^2	0.9956	0.9005	0.5730

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

To enhance the reliability of the estimation results, this paper conducts robustness testing by employing techniques such as shrinking sample capacity, shrink-tailed regression, and replacing core explanatory variables, as detailed in Table 5. Firstly, the sample capacity is shrunk by excluding the four regions of Beijing, Shanghai, Guangdong, and Hainan, where agricultural activities are not concentrated. The regression is then conducted, and the results are presented in model (7). Secondly, shrink-tailed regression eliminates abnormal data in individual years that may bias global estimation results. All variables in the model undergo 1% shrink-tailed treatment, and the resulting outcomes are displayed in model (8). Finally, the core explanatory variables are replaced, with carbon emissions resulting from fertilizers used as a proxy variable for FNSP [77,78]. The results are then presented in model (9). The impact coefficients of farmland transfer in the three models above are consistently negative and significant at the 1% level, confirming the credibility of the previous estimation results.

Table 5. Result of robustness test.

Variables	Model (7)	Model (8)	Model (9)
Transfer	−0.440 *** (0.127)	−0.461 *** (0.118)	−0.404 *** (0.117)
Constant	3.329 *** (0.607)	1.056 * (0.572)	2.117 *** (0.551)
Control variables	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Observations	400	480	480
R^2	0.9962	0.9948	0.9933

Note: *** and * indicate significance at the 1% and 10% levels, respectively. Standard errors are in parentheses.

4.4. Heterogeneity Analysis

Firstly, the provinces were categorized into primary grain-producing areas, primary grain-marketing areas, and areas of grain balance [79]. The results are displayed in model (10), model (11), and model (12) in Table 6. Farmland transfer exhibits a significant pollution reduction effect in primary grain production areas. Conversely, within primary grain marketing areas and grain balance areas, although the regression coefficients of farmland transfer remained negative, none attained statistical significance. This discrepancy can be attributed to the relatively flat terrain and concentrated, continuous cultivation characterizing primary grain production areas, which facilitate the promotion and advancement of farmland transfer, thereby fully exploiting the inhibitory effect of farmland transfer on FNSP. In contrast, within primary grain marketing areas and grain balance areas, the prevalence of farmland fragmentation and dispersion is more pronounced, hindering the realization of the scale effect generated by farmland [80].

Table 6. Results of heterogeneity analysis.

Variables	Model (10) Production	Model (11) Marketing	Model (12) Balance	Model (13) Plain	Model (14) Mountain
Transfer	−0.351 *** (0.102)	−0.298 (0.205)	−0.062 (0.279)	−0.353 ** (0.157)	−0.510 *** (0.148)
Constant	1.046 (0.817)	0.002 (0.953)	3.973 *** (1.062)	1.054 (0.796)	4.701 *** (0.616)
Control variables	Yes	Yes	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes	Yes
Observations	208	112	160	240	240
R^2	0.9901	0.9951	0.9951	0.9957	0.9974

Note: *** and ** indicate significance at the 1% and 5% levels, respectively. Standard errors are in parentheses.

Secondly, based on the classification of topographic features, the provinces were segmented into plain and mountainous regions [71,81], with separate regressions conducted for each category. The results are detailed in model (13) and model (14) in Table 6. The impact of farmland transfer on FNSP is significantly negative in both plains and mountainous areas, with a larger regression coefficient observed in mountainous regions. This finding diverges from conventional perceptions. A plausible explanation lies in the fact that mountainous areas encompass approximately one-third of the national cultivated land area. In these regions, farmland transfer can effectively mitigate abandonment phenomena, thereby restoring hilly areas' ecological nutrient functions and reducing FNSP [82].

4.5. Mechanism of the Impact of Farmland Transfer on FNSP

The results elucidating the mechanism of farmland transfer on FNSP are depicted in Table 7. As per model (15), farmland transfer significantly diminishes fertilizer application intensity [83]. Subsequently, in model (17), it is observed that fertilizer application intensity exerts a significant reduction on FNSP. Hence, farmland transfer reduces FNSP by curtailing fertilizer application intensity.

Table 7. Mechanisms of farmland transfer affecting FNSP.

Variables	Model (15) *Intensity*	Model (16) *Compound*	Model (17) *FNSP*	Model (18) *FNSP*
Transfer	−0.407 *** (0.004)	0.052 ** (0.024)	−0.332 *** (0.092)	−0.374 *** (0.114)
Intensity			0.615 *** (0.044)	
Compound				−0.837 *** (0.231)
Constant	−2.907 *** (0.478)	0.570 *** (0.112)	2.610 *** (0.457)	1.890 *** (0.551)
Sobel-Godman statistic			−0.250 ***	−0.044 *
Control variables	Yes	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
Observations	480	480	480	480
R^2	0.9499	0.9341	0.9965	0.9953

Note: ***, **, and * indicate significance at the 1%, 5%, and 10%, levels, respectively. Standard errors are in parentheses.

Moreover, model (16) indicates that farmland transfer significantly increases the compound fertilizer application. Conversely, model (18) highlights that compound fertilizer application significantly increases FNSP. Consequently, while farmland transfer boosts the compound fertilizer application, thus enhancing FNSP, the overall impact of farmland transfer on FNSP remains negative.

The stability of the mediating effect is further examined through the Bootstrap and Sobel-Goodman methods, with results detailed in Table 8 confirming the existence of the mediating effect. The mediating utility ratio is calculated at 43.01% and 10.34%, respectively. In summary, farmland transfer suppresses FNSP through two pathways: by reducing fertilizer application intensity and by increasing compound fertilizer application. Therefore, Hypothesis 2 is validated.

Table 8. Results of the mediating-effect test.

Variables	Bootstrap Test		Sobel Test		
	Observation	95% Interval	Indirect	Direct	Total
Intensity	−0.250	[−0.379, −0.095]	−0.250 ***	−0.332 ***	−0.582 ***
Compound	−0.044	[−0.089, −0.007]	−0.044 *	−0.374 ***	−0.418 ***

Note: *** and * indicate significance at the 1% and 10% levels, respectively.

4.6. Spatial Spillover Effects of Farmland Transfer on FNSP

This paper employs the spatial neighbor matrix W_1, spatial geographic distance matrix W_2, and spatial geographic distance square matrix W_3 to calculate the global Moran index of farmland transfer and FNSP, as presented in Figure 4. Across the three matrices, Moran's I of farmland d transfer exhibits a gradual expansion from 2005 to 2020, suggesting a continuous strengthening of spatial aggregation among regions [84]. Moran's I of FNSP displays a positive trend from 2005 to 2020, signifying an intensified pollution interaction among regions [85]. Overall, the observed spatial correlation between farmland transfer and FNSP suggests a relationship warranting further analysis using spatial econometric models.

This paper employs a comprehensive approach utilizing the LM test, LR test, Wald test, and Hausman test to determine the specific form of the spatial econometric model (Table 9). Initially, the statistical values of both LM and robust LM tests are significant at the 1% level, indicating the necessity of a spatial econometric model. Additionally, the Hausman test passes the 1% level test, suggesting the use of a fixed-effect model. Combined with the results of the LR test, selecting a two-way fixed SDM is more reasonable. Secondly, the statistical value of the Wald test is significant at the 1% level, indicating that SDM will not degenerate into SEM or SAR. In summary, a two-way fixed-effect SDM model is selected to analyze the spatial spillover effect of farmland transfer on FNSP.

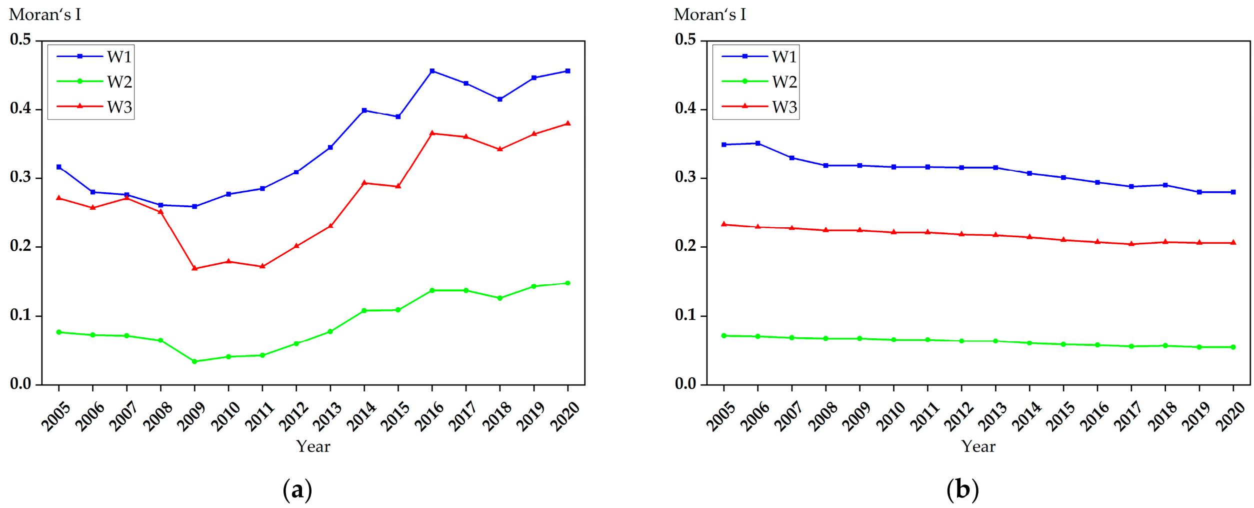

Figure 4. Moran's I of farmland transfer and FNSP. (**a**) Farmland transfer; (**b**) FNSP.

Table 9. Results of spatial econometric model tests.

Test Method	Test Name	Test Statistic W1	Test Statistic W2	Test Statistic W3
LM test	LM–Error	161.231 ***	1124.035 ***	81.973 ***
	LM–Error Robust	109.048 ***	15.134 ***	9.774 ***
	LM–Lag	94.080 ***	114.541 ***	101.177 ***
	LM–Lag Robust	41.914 ***	5.640 **	28.978 ***
LR test	LR–Both–Ind	101.360 ***	75.980 ***	67.890 ***
	LR–Both–Time	1714.060 ***	1911.540 ***	1774.920 ***
	LR–SDM–SEM	88.630 ***	60.390 ***	39.460 ***
	LR–SDM–SAR	136.680 ***	75.120 ***	67.370 ***
Wald test	Wald–SDM–SEM	84.110 ***	59.900 ***	34.760 ***
	Wald–SDM–SAR	136.010 ***	82.270 ***	72.830 ***
Hausman test	Hausman	46.430 ***	30.380 ***	44.160 ***

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.

The results in Table 10 indicate that the coefficients of farmland transfer are all significantly negative and remain so after the introduction of *W* factors. This preliminary evidence suggests the presence of spatial spillover in the inhibitory effect of farmland transfer on FNSP. However, relying solely on point estimate parameters to measure the degree of influence may lead to bias due to the presence of the spatial lag term. Therefore, it is necessary to decompose the total effect, direct effect, and spillover effect. The decomposition results reveal that under three matrices, the total effects of farmland transfer on FNSP are −1.428, −1.151, and −1.399, respectively. The direct effects are −0.225, −0.304, and −0.268, respectively. The indirect effects are −1.203, −0.847, and −1.130, respectively. The coefficients of each effect pass the significance test. These findings further indicate that the inhibitory effect of farmland transfer on FNSP exhibits a strong spatial spillover effect. This effect significantly reduces FNSP within the region and generates environmental benefits in other regions, thus validating hypothesis 3.

Table 10. Results of SDM and decomposition effects.

Variables	Model (19): W_1 Ratio	Std. Err.	Model (20): W_2 Ratio	Std. Err.	Model (21): W_3 Ratio	Std. Err.
Transfer	−0.171 *	0.103	−0.283 ***	0.110	−0.225 **	0.100
$W \times$ *Transfer*	−0.914 ***	0.216	−0.008 ***	0.157	−0.753 ***	0.214
Direct effect	−0.225 **	0.107	−0.304 ***	0.110	−0.268 ***	0.101
Indirect effect	−1.203 ***	0.274	−0.847 *	0.436	−1.130 ***	0.286
Total effect	−1.428 ***	0.310	−1.151 ***	0.426	−1.399 ***	0.306
Control variables	Yes		Yes		Yes	
Individual fixed	Yes		Yes		Yes	
Time fixed	Yes		Yes		Yes	
Spatial rho	0.235 ***	0.057	0.745 ***	0.050	0.306 ***	0.076
Observations	480		480		480	
R^2	0.2457		0.3169		0.0664	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.7. Nonlinear Effect of Farmland Transfer on FNSP

To further explore the nonlinear characteristics of the effect of farmland transfer on FNSP, a threshold effect test is conducted to determine the number of potential thresholds. Stata 18.0 software is utilized to conduct the Bootstrap method, randomly sampling 300 times for the threshold effect test. The results are presented in Table 11. Both single and double thresholds passed the 1% level test. Furthermore, after separately plotting the LR diagram of the two thresholds, it is observed that both thresholds pass the test with a 95% confidence interval (Figure 5). Therefore, the nonlinear relationship between farmland transfer and FNSP shows a double threshold.

Table 11. Results of threshold model test.

Threshold Test	Threshold Value	Conversion Value	F Statistic	*p* Value
Single threshold	0.199	0.220	83.050 ***	0.000
Double threshold	0.344	0.411	46.350 ***	0.000
Triple threshold	0.472	0.603	27.730	0.330

Note: *** indicate significance at the 1% levels, respectively.

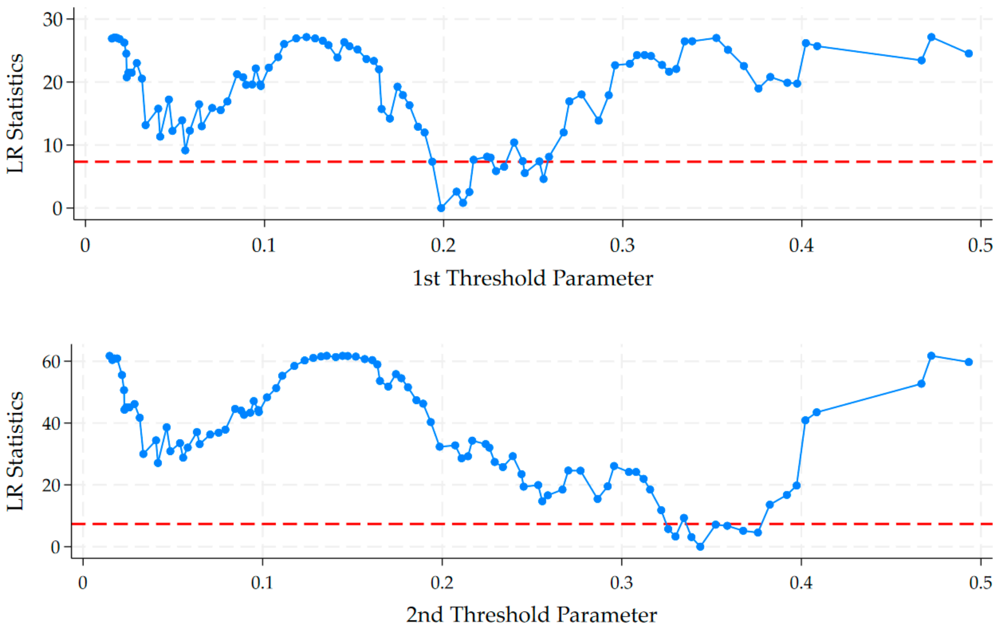

Figure 5. LR test for threshold model. Note: Red dashes represent 95% confidence level.

Table 12 results indicate that when farmland transfer is below the first threshold value of 0.344 (corresponding to a proportion of actual farmland transfer less than 0.411), the inhibitory effect on FNSP is insignificant. For farmland transfer between 0.344 and 0.472 (corresponding to a proportion of actual farmland transfer between 0.411 and 0.603), the coefficient is −0.467, passing the 1% level test. This indicates significant inhibition of FNSP within this interval. For farmland transfers exceeding 0.472 (corresponding to a proportion of actual farmland transfer greater than 0.603), the regression coefficient is −0.970, significant at the 1% level. This signifies an intensified inhibitory effect of farmland transfer on FNSP after surpassing the second threshold. In summary, the effect of farmland transfer on FNSP is nonlinear.

Table 12. Regression results of the threshold model.

Variables	Coefficient	T Value	95% Confidence
Transfer (*Transfer* < 0.344)	−0.044	−0.460	[−0.193, 0.119]
Transfer (0.344 ≤ *Transfer* ≤ 0.472)	−0.467 ***	−6.510	[−0.587, −0.308]
Transfer (*Transfer* > 0.472)	−0.970 ***	−11.370	[−1.128, −0.797]
Constant	0.398	0.910	[−0.256, 1.454]
Control Variables		Yes	
F(29, 441)		661.020 ***	
Observations		480	
R^2		0.4756	

Note: *** indicate significance at the 1% levels, respectively. Standard errors are in parentheses.

Additionally, this study selects 2005, 2010, 2015, and 2020 as representative years. Provinces across the country are divided based on actual thresholds, with the results depicted in Figure 6. Overall, there is a gradual increase in the number of provinces crossing the threshold. In 2005, all of the provinces remained within the threshold. In 2010, only Beijing and Shanghai crossed the first threshold, while the remaining provinces remained below it. In 2015, Shanghai and Jiangsu crossed the second threshold. Beijing, Heilongjiang, Zhejiang, Anhui, and Chongqing were between the first and second thresholds. In 2020, Shanghai, Beijing, Jiangsu, and Chongqing crossed the second threshold. Most other provinces were within the first threshold. Zhejiang, Heilongjiang, Tianjin, Anhui, Jiangxi, Guangdong, Shandong, and Hunan were between the first and second thresholds.

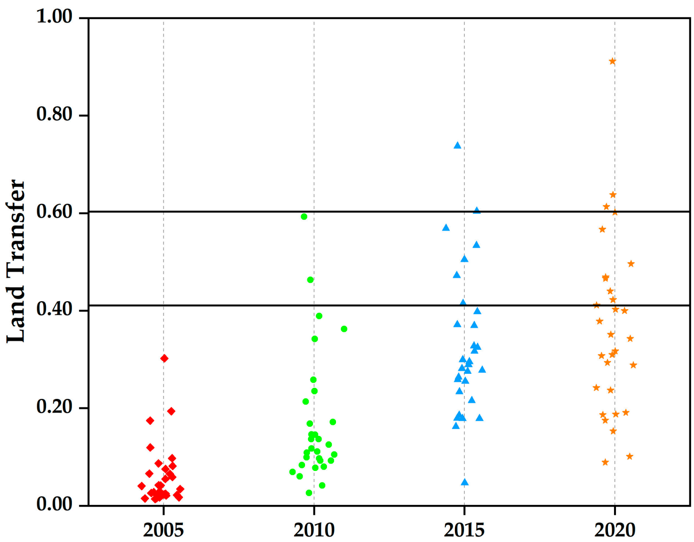

Figure 6. Comparison of farmland transfer and threshold by province.

5. Discussion

5.1. Comparison with Related Studies

This paper found that farmland transfer can significantly inhibit pollution caused by fertilizer application [86], which is similar to the findings of Guo et al. [87] and Lu et al. [88]. Farmland transfer is an essential means of expanding the scale of operation [89]. The scale of operation contributes to reducing chemical fertilizers; for example, Ren et al. analyzed data from China and pointed out that the scale of agricultural operation up to 3.8 hectares could save 45% of chemical fertilizers [90]. Similarly, Guo et al. concluded that for every 1% increase in cropland area, nitrogen fertilizer application would be reduced by 0.93% [91]. These studies are similar to the main points of this paper. However, these studies should have considered the heterogeneous effects of differences in land types, natural conditions, and other factors on fertilizer loss, and the fertilizer loss rate determined using fertilizer application intensity and the application ratio may also lead to inaccurate estimation results. Therefore, this paper used a more scientific method to measure FNSP and integrated multiple econometric models to verify the inhibitory effect of farmland transfer on FNSP.

In terms of the influence mechanism, this paper argues that reducing the application intensity of chemical fertilizer and increasing the application ratio of compound fertilizer has a mediating effect on the process of farmland transfer, inhibiting FNSP. First, farmland transfer can significantly reduce the intensity of chemical fertilizer application [83], which was verified by Cao et al. [89] and Xu et al. with microdata [92]. Secondly, farmland transfer contributes to compound fertilizer application, which is similar to the findings of Li et al. [93] and different from those of Shang et al. [94]. In addition, this paper found a spatial spillover of the inhibitory effect of farmland transfer on FNSP, and existing studies have reached similar conclusions [72,95].

5.2. Implications for Policymakers

Drawing from this study, several policy insights emerge. Firstly, there is a crucial need to acknowledge the scale economies and environmental benefits of farmland transfer. This entails bolstering the rural land transaction market, enhancing mechanisms for resolving land disputes, and reinforcing support for large-scale agricultural producers. Secondly, enhancing regional coordination throughout the farmland transfer process is imperative. Facilitating inter-regional communication and collaboration within the agricultural sector and expediting the refinement of compensation mechanisms for promoting green agricultural development is paramount. Finally, it is essential to actualize the high-quality development of farmland transfer. This necessitates adhering to principles of moderate-scale operation, transforming agricultural management practices, and enhancing the efficiency of agricultural production factor allocation to mitigate the risks of low-quality or spurious transfers.

5.3. Limitations of the Study and Future Prospects

This paper contributes to existing studies by integrating farmland transfer and FNSP into a unified analytical framework, systematically exploring their relationship. While this paper analyzes the impact of farmland transfer on FNSP using macro statistical data, further elucidation of the specific mechanism requires field research or experimental design. Future research should undertake a more detailed and in-depth analysis by investigating or comparing micro-level farmland transfer activities and FNSP using microdata.

The analysis in this paper reveals heterogeneity in the impact of farmland transfer on FNSP. However, only regional heterogeneity is addressed due to the limitations of macro panel data, and further analysis on the heterogeneity of the impact of farmland transfer on different land types and transfer types is needed. Future research should conduct a more in-depth analysis of the impact of farmland transfer heterogeneity on FNSP by further integrating medium and micro data.

6. Conclusions

This study assesses the FNSP of each province in mainland China by analyzing panel data from 2005 to 2020, encompassing 30 provinces. Various models including the fixed-effect model, the mediating-effect model, the spatial Durbin model, and the threshold regression model are constructed to empirically investigate the impact of farmland transfer on FNSP. The primary findings are as follows:

Firstly, farmland transfer demonstrates significantly inhibited FNSP, which persists even after accounting for endogeneity and conducting robustness tests. Moreover, this effect exhibits regional heterogeneity, manifesting a notable reduction in pollution in primary grain production areas, yet lacking significance in primary grain marketing and grain balancing areas. Notably, the inhibitory effect is more pronounced in mountainous regions than in plains.

Secondly, the environmental effects triggered by farmland transfer involve mediation, predominantly through two pathways: reducing fertilizer application intensity and increasing compound fertilizer application, both contributing to the inhibition of FNSP.

Thirdly, farmland transfer significantly mitigates FNSP within its own region and induces neighboring regions to decrease FNSP, illustrating a substantial spatial spillover effect.

Lastly, a double-threshold nonlinear relationship between farmland transfer and FNSP is identified. FNSP suppression occurs only beyond a certain threshold of farmland transfer, with larger-scale transfers correlating with stronger suppression effects.

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