

Article

Analysis of Spatial Distribution and Spillover Effects of Fertilizer Application Intensity in Inner Mongolia, China

Benna Da ¹, Yunhua Wu ^{1,*} and Wuyuntana Bao ²

¹ College of Economics and Management, Inner Mongolia Agricultural University, Hohhot 010018, China; dabenna1993@163.com

² School of Accounting, Inner Mongolia University of Finance and Economics, Hohhot 010018, China; baowyt@163.com

* Correspondence: nm_wyh@imau.edu.cn

Abstract: The overuse of fertilizers has caused significant environmental pollution. In this paper, we aim to improve fertilizer utilization and promote sustainable agricultural development. Based on panel data at the flag (county) level in Inner Mongolia from 2001 to 2020, we analyzed the spatial heterogeneity and correlation of fertilizer application intensity using a two-stage nested Theil index and Moran's *I*, and employed a Durbin model to elucidate its spatial spillover effects. The results show that overall disparities in fertilizer application intensity showed a decreasing trend, with league (city) disparities being the main reason for the overall disparities. In terms of spatial patterns, there is a positive spatial correlation between flags (counties), with the western region exhibiting a “high-high” type that gradually shifts towards the eastern region, particularly the cities of Tongliao and Chifeng. The central and eastern regions exhibit a “low-low” type. Future endeavors to decrease fertilizer application intensity are mainly focused on establishing “high-high” clusters. Policymakers should leverage these spatial interactions to diminish fertilizer usage and mitigate environmental pollution. Farmers, affluence, agricultural economic development, and grain yield positively influence fertilizer application intensity while agricultural modernization and land size have negative effects. All these factors demonstrate significant spatial spillover effects.

Keywords: fertilizer application intensity; regional disparities; spatiotemporal evolution; spillover effect; spatial Durbin model



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1. Introduction

Since China's reform and opening up, its agricultural sector has seen remarkable increases in output value. Fertilizers have played a pivotal role in this progress, which has been demonstrated by research. Since the 1960s, the application of fertilizers has resulted in a roughly 260% growth in grain output [1]. Correspondingly, China is the world's largest producer and consumer of fertilizers [2]. Fertilizer application in China is 328.5 kg per hectare, far exceeding the global average of 120 kg per hectare [3]. This excessive use of fertilizer has resulted in various non-point source pollution issues, such as soil compaction [4], the eutrophication of water bodies [5], and heavy metal contamination of the soil [6]. As products of technological progress, fertilizers are essentially harmless. The problem does not lie solely with chemical fertilizers themselves but stems from their unreasonable and unscientific application [7]. According to research, the augmentation of fertilizer application in China is primarily driven by the enhancement of fertilizer application intensity [8]. Lowering fertilizer application intensity faces more challenges [7]. The objective should be to transition from “reducing total quantity” to “lowering intensity”. China's government has shown a commitment to enhancing fertilizer use efficiency. In 2015, the former Ministry of Agriculture proposed the “Action Plan for Zero Growth in Fertilizer Use by 2020”, which was subsequently incorporated into the “13th Five-Year

Plan". Thus, China has been pursuing a reduction in fertilizer volume while aiming to enhance efficiency.

Over the years, the academic community has conducted a significant amount of innovative research from various perspectives on fertilizer application intensity. From the perspective of research methodology, some studies have developed tools to assess the environmental hazards of fertilization and set safety thresholds to evaluate the potential risks and sustainability of fertilizer use [2]. Other scholars first utilized the SBM model to measure fertilizer utilization efficiency, followed by employing methods such as the Theil index, Kernel density estimation, and Markov chain analysis to examine spatial disparities and dynamic distribution evolution [9]. Additionally, scholars explored the migration patterns of fertilizer application centers, spatial relationships, and regional disparities in characteristics using spatial relationship models, gravity models, entropy weighting methods, and more [10]. Certain academics employed factor decomposition methodology to holistically dissect the influencing factors of agricultural carbon emission intensity [11]. They then employed general equilibrium models to simulate the potential effects of fertilizer reduction policies on both agricultural production and environmental pollution [12]. From the perspective of research scope, studies have investigated the extent of fertilizer use in various regions, including the intensity of fertilizer application in major grain-producing regions [13], in rice-growing areas [14], and in the Taihu Lake Basin [4].

Below is an analysis of the relationship between soil fertility and sustainable agricultural development. Over 40% of China's arable land has begun to suffer from salination and soil erosion [15]. With a growing understanding of the pollution and loss of arable land, scholars have begun to focus on the stability of agricultural productivity [16] and issues concerning agricultural sustainability [17]. This is mainly due to the inappropriate structure of fertilizer application, with farmers often favoring chemical fertilizers over organic ones and neglecting the proper balance of nitrogen, phosphorus, and potassium. This practice not only harms soil fertility but also affects crop nutrient uptake, thus posing a threat to agricultural sustainability [18,19]. Furthermore, some studies have examined the impact of chemical fertilizer use on agricultural non-point source pollution, greenhouse gases, and other factors [20,21]. As agricultural pollution worsens, sustainable agricultural development faces threats, prompting China to prioritize ecological protection, emphasizing that "protection takes precedence over development" [22]. Numerous academics are committed to elucidating the equilibrium between the value of ecosystems and economic development [23]. Simultaneously, researchers have analyzed the connection between ecological benefits and sustainable, high-quality development [24].

From the perspective of influence factors, the increase in fertilizer application rates is the result of the combined influence of natural, social, and economic factors. The intensity of the supply and demand relationship for fertilizers is also on the rise, with natural, social, and economic factors playing a promoting role in this trend [25]. However, studies have shown that directly reducing fertilizer application rates can increase land use intensity. The key lies not in simply cutting down on fertilizer usage but in moderating the intensity of its application [26]. As land scale increases, the intensity of fertilizer application decreases [27]. The relationship between scale farming and fertilizer application is non-linear. Fertilizer application intensity varies in a U-shape pattern with farming scale, meaning that moderate-scale farming can reduce fertilizer intensity, while excessively large-scale farming can increase it [28]. There is a "U-shaped" inverse relationship between fertilizer usage and yield [29]. Meanwhile, circular agriculture can decouple yield increase from resource consumption, where yield growth no longer relies on resource consumption. Circular agriculture can fundamentally address the contradiction between yield increase and environmental pollution [30]. Additionally, fertilizer intensity is influenced by individual characteristics, information acquisition capabilities, and policy guidance [25,31–33], as well as regional spatial characteristics, economic levels, population, technological levels, and other factors [2,34]. Thus, there is substantial practical value in further investigating the mechanisms influencing fertilizer application intensity.

Given the valuable theoretical basis that existing research has provided for the sustainable development of agriculture, there still exists space for further investigation. In light of this, the contributions of this study are summarized as follows: (1) Existing studies primarily focus on the calculation and analysis of fertilizer application intensity, as well as exploring the influence and effects of one or more factors on fertilizer application intensity. However, these studies have not adequately considered the impacts of population, economy, and technology on fertilizer application intensity. This paper employs the STIRPAT environmental assessment model as a theoretical framework to analyze the factors influencing fertilizer application from the perspectives of population, affluence, and technology. It aims to provide reliable evidence for elucidating the driving factors behind the increase in fertilizer application intensity. Additionally, it employs spatial econometric models to analyze the factors influencing fertilizer application intensity and the resulting spatial spillover effects. This investigation holds significance in elucidating the drivers behind the escalation of fertilizer application intensity and comprehending the mechanisms of spatial spillover effects, thereby furnishing scientific groundwork for devising fertilizer reduction policies. (2) Existing studies have overlooked the spatial factors influencing fertilizer application intensity, yet the diffusion of fertilizer application can lead to spatial spillover effects causing environmental pollution. This study adopts a spatial perspective, focusing on Inner Mongolia, to investigate the spatial correlation and clustering of fertilizer application intensity using the Theil index and Moran's *I* tests. Additionally, this research employs spatial econometric models to analyze the influencing factors of fertilizer application intensity and the spatial spillover effects it generates. This study provides a scientific basis for the formulation of targeted fertilizer reduction policies.

2. Materials and Methods

2.1. Study Area

Inner Mongolia is located on the northern frontier of China and has a total area of 1.183 million square kilometers, accounting for 12.3% of the total land area of China, making it the third largest province in China (Figure 1). According to China's meteorological and geographical zoning, it is divided into three regions: eastern, central, and western Inner Mongolia. The eastern region includes four leagues (cities): Hulunbuir, Xing'an, Tongliao, and Chifeng. The central region comprises three leagues (cities): Xilingol, Ulanqab, and Hohhot. The western region includes five leagues (cities): Baotou, Bayannur, Ordos, Wuhai, and Alxa. Inner Mongolia experiences a temperate continental monsoon climate, exhibiting clear seasonal distinctions. Spring is characterized by windy conditions and limited rainfall, while summer is hot and dry. Autumn arrives early with frost, and winter is cold and protracted. Inner Mongolia is predominantly characterized by plateau topography, with plateaus occupying roughly 50% of its total land area. The plains cover about 8% of the total area and include the Nen River West Bank Plain, the West Liao River Plain, the Tumochuan Plain, the Hetao Plain, and the Yellow River South Bank Plain. These plains are characterized by fertile soil, ample sunlight, and abundant water sources, making them the primary regions for grain and economic crop cultivation in Inner Mongolia. Mountainous regions constitute around 20% of the territory, while hills account for about 16%. Water bodies such as rivers, lakes, and reservoirs cover roughly 0.8% of the area. The soil types in Inner Mongolia mainly include 22 types, such as brown soil, dark brown soil, gray-brown soil, and black soil, with black soil being the most fertile. Soil fertility gradually decreases from the northeast to the southwest. This unique resource endowment and the natural conditions have positioned Inner Mongolia as a crucial ecological security barrier in northern China and as one of the major grain-producing regions nationwide.

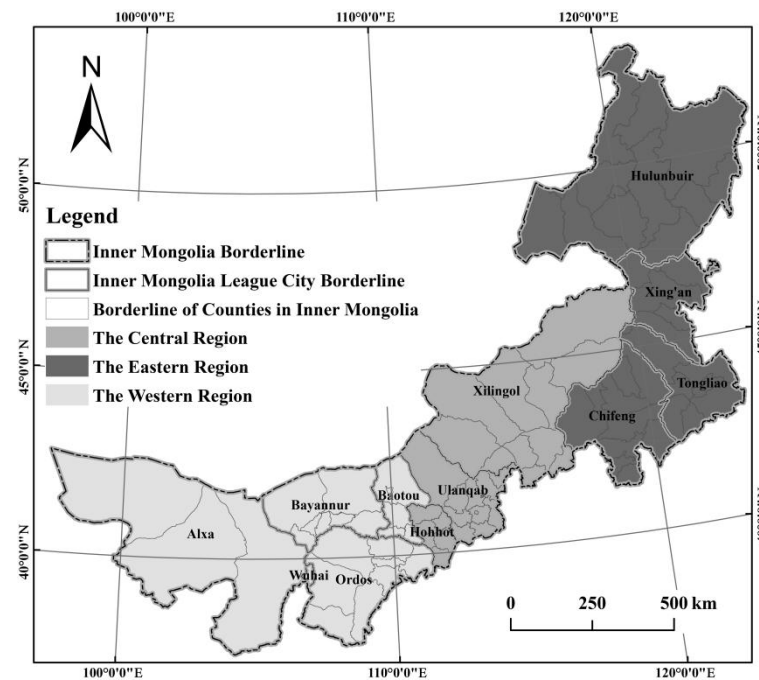


Figure 1. Location of the study area.

2.2. Materials

Statistical Data

Data are sourced from the Inner Mongolia Statistical Yearbook and the statistical yearbooks of 12 leagues (cities) in Inner Mongolia, covering 2001–2020. Because of missing data, Baiyun’ebo Mining District, Kangbashen, Abag Banner, and Zhalainuo’er District are excluded from the analysis. A total of 99 banners (counties) spanning 20 years are included in the panel dataset. Spatial vector data from the National Basic Geographic Information Center and ArcGIS 10.8 software were utilized to generate vector maps.

2.3. Methods

2.3.1. Theil Index

We used the Theil index to evaluate regional disparities in fertilizer application intensity in Inner Mongolia. The main advantage of the Theil index is its ability to decompose overall disparities into within-region and between-region disparities, providing a more comprehensive understanding of variations in fertilizer application intensity across diverse regions and their contributions to the overall disparities [35,36].

First, taking leagues (cities) as the basic research unit, we used the one-stage Theil index to measure the fertilizer application intensity of overall, inter-regional, and intra-regional disparities. The formula is as follows:

$$T_1 = \frac{1}{m} \sum_i \sum_j \frac{P_{ij}}{Q} \log \frac{P_{ij}}{Q} = \frac{1}{m_1} \sum_i \frac{m_i Q_i}{m Q} \sum_j \frac{P_{ij}}{Q_i} \log \frac{P_{ij}}{Q_i} + \sum_i \frac{m_i Q_i}{m Q} \log \frac{Q_i}{Q} = T_{WR} + T_{BR}, \quad (1)$$

where T_1 represents the one-stage Theil index, m represents the number of leagues (cities), P_{ij} represents the fertilizer application intensity of league (city) j in region i , Q represents the average value of fertilizer application intensity in Inner Mongolia, Q_i represents the average value of fertilizer application intensity in region i , T_{WR} represents intra-regional disparities, and T_{BR} represents inter-regional disparities.

Then, taking flags (counties) as the basic research unit, we used the two-stage nested Theil index to further disaggregate intra-regional disparities into intra-league (city) and inter-league (city) disparities. The aim is to assess fertilizer application intensity across all regions and quantify disparities in fertilizer application intensity between regions, among cities within the same region, and among cities in different regions [37]. The formula is as follows:

$$T_2 = \frac{1}{m} \sum_i \sum_j \sum_k \frac{P_{ijk}}{Q} \log \frac{P_{ijk}}{Q} = \frac{1}{m_{ij}} \sum_i \sum_j \frac{m_{ij} Q_{ij}}{mQ} \sum_k \frac{P_{ijk}}{Q_{ij}} \log \frac{P_{ijk}}{Q} + \sum_i \frac{m_i Q_i}{mQ} \sum_j \frac{m_{ij} Q_{ij}}{m_i Q_i} \log \frac{Q_{ij}}{Q_i} + \sum_i \frac{m_i Q_i}{mQ} \log \frac{Q_i}{Q} = T_{WF} + T_{BF} + T_{BR}, \quad (2)$$

where T_2 represents the two-stage nested Theil index, k represents k flags (counties), T_{WF} represents inter-league (city) disparities, T_{BF} represents intra-league (city) disparities, and T_{BR} represents inter-regional disparities.

2.3.2. Spatial Correlation Analysis

We used the global Moran's I to test the spatial correlation in fertilizer application intensity. We also used the local Moran's I to present the local variation characteristics and significance level.

Global Moran's I calculation formula:

$$\frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}}, \quad (3)$$

where $S^2 = \frac{1}{n} \sum_{i=1}^n (\sum_{i=1}^n (y_i - \bar{y}))^2$, $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$; n represents the number of spatial units; Y_i and Y_j represent the observed values for regions i and j , respectively; $\bar{Y}$ represents the mean value; and W_{ij} represents the spatial weight matrix. The global Moran's I take values in the range of $[-1, 1]$. Under the condition of a significance level, when global Moran's $I > 0$, it indicates a positive spatial correlation between regions; when global Moran's $I < 0$, it indicates a negative spatial correlation; when global Moran's $I = 0$, it means there is no spatial correlation.

We used the Z-value to test the significance of Moran's I :

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}}, \quad (4)$$

where $Z(I)$ is the test statistic, $E(I)$ is the expected value, and $Var(I)$ is the variance.

The calculation formula for local Moran's I is

$$\frac{n \left[(Y_i - \bar{Y}) \sum_{j=1}^n W_{ij} (Y_j - \bar{Y}) \right]}{\sum_{i=1}^k (y_i - \bar{y})^2}. \quad (5)$$

The local Moran's I is presented through LISA cluster maps, which depict four types of clusters: "high-high", "low-high", "low-low", and "high-low".

2.3.3. Spatial Durbin Model

Dependent Variable

Fertilizer application intensity is the dependent variable, calculated by dividing the total amount of fertilizer applied in each Inner Mongolian flag (county) by the area of crop cultivation, with fertilizer quantity measured based on its pure nutrient content (Table 1).

Table 1. Definitions of all variables in the spatial Durbin model.

Variable Type	Abbreviation	Name	Definition
Dependent variables	FAI	Fertilizer application intensity	Amount of fertilizer applied/crop-sowing area
Independent variables	LAB	Labor	Amount of rural labor force
	AFFL	Affluence level	Per capita net income of rural residents
	MECH	Modernization level	Total power of agricultural machinery
	AEL	Agricultural economic level	Value of primary industry output/GDP (%)
	AS	Agricultural scale	grain production scale (GS) cultivated land area scale (LS)

Independent Variable

Drawing on the existing literature on the influencing factors of agricultural fertilizer application intensity [38–41], this study, from an economic perspective, adopts the STIRPAT environmental assessment model as the basis and selects the following influencing factors (Table 1).

Labor force: In this paper, ‘labor force’ refers to the population in rural areas capable of working (males aged 16–60, females aged 16–55). Fertilizer application constitutes a crucial stage in agricultural production, demanding considerable time and energy. Hence, in situations of time and energy constraints, farmers might resort to applying large amounts of fertilizer at once to ensure yield. Both the quantity and quality of the rural labor force influence fertilizer application intensity [42]. Regarding quality, regions with a higher proportion of working-age adults and fewer elderly and female workers are better positioned to possess the physical and manpower prerequisites for rational fertilizer application. In terms of quantity, regions with fewer non-agricultural labor force migrations may witness farmers investing more effort in agriculture, thereby emphasizing the rational utilization of fertilizers.

Level of prosperity: This is represented by the per capita net income of rural residents. Growth economics suggests that economic growth relies primarily on inputs of production factors, with inputs in agricultural production factors effectively increasing output. As farmers’ income increases, they are more likely to actively increase inputs of production factors in pursuit of stable or even higher yields. However, the Environmental Kuznets Curve suggests that once income exceeds a certain threshold, farmers tend to reduce environmental pollution. Further empirical tests will be conducted to verify these propositions.

Level of agricultural modernization: This is represented by the total power of agricultural machinery. The increase in the level of agricultural mechanization in a region can effectively drive the ‘reduction of fertilizer usage’ initiative. Regions with high levels of agricultural mechanization can enhance fertilizer application efficiency and reduce fertilizer application intensity. For instance, techniques such as mechanized deep plowing can effectively reduce fertilizer usage while increasing efficiency. It is expected that a higher total power of agricultural machinery will lead to an increase in fertilizer application intensity.

Agricultural economic weight: This is represented by the contribution of the primary sector output value to GDP. In regions where agriculture dominates, the increase in agricultural output may prompt local governments to continue increasing fertilizer inputs to enhance agricultural competitiveness. However, under the influence of national policies and support, there may be a shift towards the development of higher-quality green agricultural products for long-term agricultural development, leading to a reduction in fertilizer application intensity. The expected impact of agricultural economic weight on fertilizer application intensity is uncertain.

Scale of agriculture: This is represented by grain production and cultivated land area. Inner Mongolia is a major grain-producing region in China, and ensuring food security is a crucial mission for Inner Mongolia, as well as the fundamental means of livelihood for farmers. On one hand, farmers’ reliance on fertilizers is to some extent dependent on output; in their pursuit of stability or increased yields, they may engage in excessive fertilizer application. It is expected that higher grain production will result in greater fertilizer application intensity. On the other hand, cultivated land forms the foundation of agricultural development. Larger land areas allow for the application of advanced machinery and techniques, which can enhance fertilizer efficiency. Thus, it is anticipated that larger cultivated land areas will lead to higher fertilizer utilization rates.

Model Setting

Generally, proximate areas exhibit stronger connections facilitated by favorable conditions for information dissemination and transportation. The first law of geography posits that, while everything is interconnected, proximity intensifies such relationships more

than distance. Based on this, the spatial econometric model considers two factors that influence each other. The first is that the movement of fertilizer is facilitated by similar resource endowments, topographical conditions, and convenient transportation between adjacent regions. If environmental regulations are strict in a particular area, it might result in increased fertilizer transfer to neighboring regions owing to limitations on agricultural production. The second factor is the similarity in agricultural industry structures between adjacent areas, which results in comparable fertilizer application structures and methods. This means that the stronger the correlation between neighboring regions, the higher the level of interaction, leading to an increased likelihood of spatial agglomeration. When selecting spatial econometric models, the establishment of the spatial weight matrix is crucial. In Inner Mongolia, the effect of fertilizer application intensity is largely influenced by the proximity of various banners (counties). The closer the distance between banners (counties), the stronger the spatial effect. Therefore, we used an inverse distance weight matrix (IDW) to construct the spatial econometric model. A value of 1 indicates adjacency between banners (counties), while a value of 0 indicates non-adjacency. To mitigate the dimensional effect of the inverse distance weight matrix, we applied standardization to ensure that the sum of elements in each row equals 1.

The three most commonly used models in spatial econometrics are the spatial autoregressive (SAR) model, the spatial error model (SEM), and the spatial Durbin model (SDM). Selecting the best model requires conducting a series of tests. SAR, SEM, and SDM are represented as follows:

$$Y = \delta WY + \beta X + \gamma, \gamma \sim N(0, \sigma^2 I_n), \quad (6)$$

$$Y = \beta X + \gamma, \gamma = \theta W\gamma + \vartheta\gamma, \vartheta \sim N(0, \sigma^2 I_n), \quad (7)$$

$$Y = \beta X + WX\rho + \gamma, \gamma = \theta W\gamma + \vartheta\gamma, \vartheta \sim N(0, \sigma^2 I_n), \quad (8)$$

where Y represents an n -dimensional vector of the dependent variable; X and $n \times k$ represent a dimensional matrix of the explanatory variables; W represents the spatial weight matrix; β is the vector of relevant parameters; δ , θ , and ρ represent the correlation coefficients; γ , ϑ represents random error terms; and I_n represents the n -order identity matrix.

Considering our research content and selected independent variables, the SDM model for this study is

$$\begin{aligned} Y_{fert} = & \alpha W \ln Y_{fert} + \beta_1 \ln \text{labor} + \rho_1 W \ln \text{labor} + \beta_2 \ln \text{Income} + \\ & \rho_2 W \ln \text{Income} + \beta_3 \ln \text{Mech} + \rho_3 W \ln \text{Mech} + \beta_4 \ln \text{Constr} + \rho_4 W \ln \text{Constr} + \\ & \beta_5 \ln GY + \rho_5 W \ln GY + \beta_6 \ln CA + \rho_6 W \ln CA + \mu_i + \mu_t + \gamma, \end{aligned} \quad (9)$$

where β represents the coefficients of the independent variables, ρ represents the coefficient of the spatial lag of the independent variable, μ_i represents individual fixed effects, and μ_t represents time-fixed effects.

3. Results

3.1. Spatiotemporal Distribution Characteristics of Fertilizer Application Intensity

Before conducting the empirical research, we aimed to identify the preliminary characteristics by describing the basic facts. The study period covers 2001–2020, with one year selected for every five years using an equidistant method. Fertilizer application intensity was divided into four levels using the natural break method: low-intensity fertilization zone ($<101.96 \text{ kg/hm}^2$), medium-intensity fertilization zone ($101.96\text{--}232.31 \text{ kg/hm}^2$), high-intensity fertilization zone ($232.31\text{--}439.12 \text{ kg/hm}^2$), and ultra-high-intensity fertilization zone ($>439.12 \text{ kg/hm}^2$).

During the study period, the spatiotemporal changes in fertilizer application intensity primarily manifested as a gradual decrease in areas with low-intensity fertilization and high-intensity fertilization, while an increase was witnessed in areas with moderate-

intensity fertilization and super-high-intensity fertilization (Figure 2). Compared to 2001, by 2020, the number of moderate-intensity fertilization areas in eastern Inner Mongolia had significantly increased, while the quantity of low-intensity fertilization areas in central Inner Mongolia had notably decreased. Moreover, the super-high-intensity fertilization areas primarily concentrated in western Inner Mongolia gradually shifted to eastern Inner Mongolia. Simultaneously, the spatial changes in fertilizer application intensity exhibited stage-wise characteristics: before 2005, there were more low-intensity fertilization areas, mainly concentrated in Xilingol League, Siziwang Banner, Chahaer Right Wing Rear Banner, and Liangcheng County of Ulanqab City in central Inner Mongolia, as well as Xin Barag Right Banner, Xin Barag Left Banner, and Ewenki Autonomous Banner of eastern Inner Mongolia. The high-intensity fertilization areas were relatively few, mainly concentrated in certain banners (counties) of Bayannur City and Ordos City. Between 2005 and 2020, the gradual replacement of low-intensity fertilization areas by moderate-intensity fertilization areas occurred. Notably, since 2005, there has been a significant increase in moderate-intensity fertilization areas in eastern Inner Mongolia. This phenomenon can be attributed to China's initiation of agricultural tax exemption in 2005. As the eastern part of Inner Mongolia is a major grain-producing region, farmers are more willing to increase input of production factors to augment their income. Simultaneously, the expansion of high-intensity fertilization areas was observed, with Alxa League and Wuhai City in western Inner Mongolia emerging as high-intensity fertilization areas. Moreover, cities such as Zhalantun, Zhalantun Banner, Keerqin Right Front Banner, Keerqin Right Middle Banner, Zaruud Banner, Kalaqin Banner, and Aohan Banner in eastern Inner Mongolia have prominently transitioned into high-intensity fertilization areas.

In Inner Mongolia, the distribution of fertilizer application intensity shows a basic trend where the central region, with low-intensity application, acts as the epicenter, gradually strengthening towards both the western and eastern regions and transitioning gradually from the western to the eastern regions. For example, in 2020, there was a notable presence of moderate-intensity fertilization areas, predominantly concentrated in the eastern region of Inner Mongolia, encompassing Hulunbuir City, Xilingol League, and Chifeng City. Similarly, in the western region, significant clusters of moderate-intensity fertilization areas are observed, including Alxa Left Banner and Alxa Right Banner of Alxa League, Urad Middle Banner and Hanggin Rear Banner of Bayannur City, Darhan Muminggan United Banner of Baotou City, and Dalad Banner of Ordos City. Following these, high-intensity fertilization areas are prominent, concentrated in parts of Tongliao City and Chifeng City in the eastern region, with a scattered presence in Ejina Banner, Zhalantun Banner, Etoke Banner, and Hanggin Banner, among others. Occasional occurrences of super-high-intensity fertilization areas are scattered across Hanggin Rear Banner, Kulun Banner, Zaruud Banner, and Keerqin Left Rear Banner. Furthermore, low-intensity fertilization areas are scarce and remain concentrated in the central region, particularly in Xilingol League.

In conclusion, the period from 2001 to 2020 witnessed a notable decline in low-intensity fertilization areas alongside a clear rise in the number of areas characterized by moderate to high fertilization intensity. Fertilizer application intensity varies over time and space owing to the developmental stage of agriculture and the degree of related policy formulation and implementation in different regions [43]. Additionally, Inner Mongolia's mixed agricultural, pastoral, and semi-agricultural semi-pastoral areas, as well as its vast geographical expanse and significant climate variations from east to west, also contribute to changes in fertilizer application intensity.

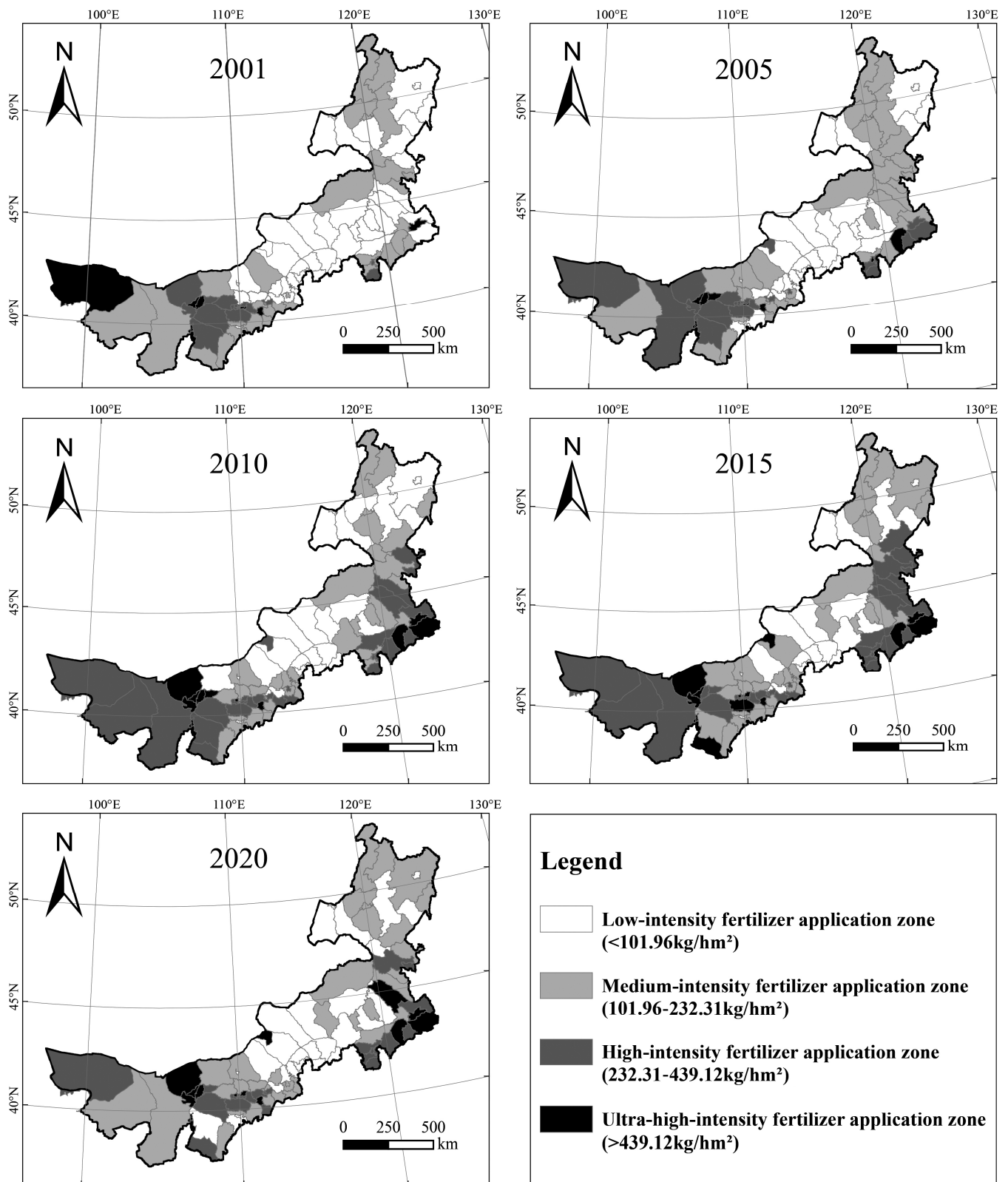


Figure 2. Spatial distribution of fertilizer application intensity in Inner Mongolia.

3.2. Regional Disparities in Fertilizer Application Intensity and Correlation Tests

3.2.1. Analysis of Regional Disparities in Fertilizer Application Intensity

Regarding the one-stage Theil index (Figure 3), overall disparities in fertilizer application intensity exhibit a narrowing trend, decreasing from 0.39 in 2001 to 0.29 in 2020, a

reduction of 26.49%. The most significant decrease is seen between 2001 and 2010. Taking 2001 and 2005 as the base years, the decrease from 2001 to 2005 was 23.6%, while from 2005 to 2010, it was 20.63%. The reduction from 2001 to 2010 primarily stemmed from the period between 2001 and 2005. The main driver behind this trend was policy intervention [12]. In order to safeguard food production, China introduced a series of fertilizer support policies starting in 2001. These policies included preferential electricity and gas prices for fertilizer production, discounted fertilizer transportation rates, and subsidies for fertilizer imports. These policies led to an increase in fertilizer usage nationwide, resulting in a significant decrease in regional disparities in fertilizer application intensity from 2001 to 2005. Starting in 2005, the government began proposing policies to address the environmental impact of excessive fertilizer use, such as the “Scheme for Reforming and Improving the Price Control Mechanism of Chemical Fertilizers” and “Notice on Further Improving the Implementation Opinions of the Dynamic Adjustment Mechanism for Comprehensive Agricultural Input Subsidies”. The effects of adjustment policies are undoubtedly slower than those of supportive policies, hence the reduction in disparities between 2005 and 2010 was smaller than that between 2001 and 2005. According to the definition of the Theil index, this decline indicates a narrowing of regional disparities in fertilizer application intensity. The average values for intra-regional disparities and inter-regional disparities are 0.22 and 0.06, respectively. The change in the trend in regional disparities is basically consistent with the change in the trend of overall disparities, with intra-regional disparities being the main source of overall disparities. The decreasing trend in overall disparities partly indicates a transition in fertilizer application practices in Inner Mongolia from extensive to precision-oriented methods.

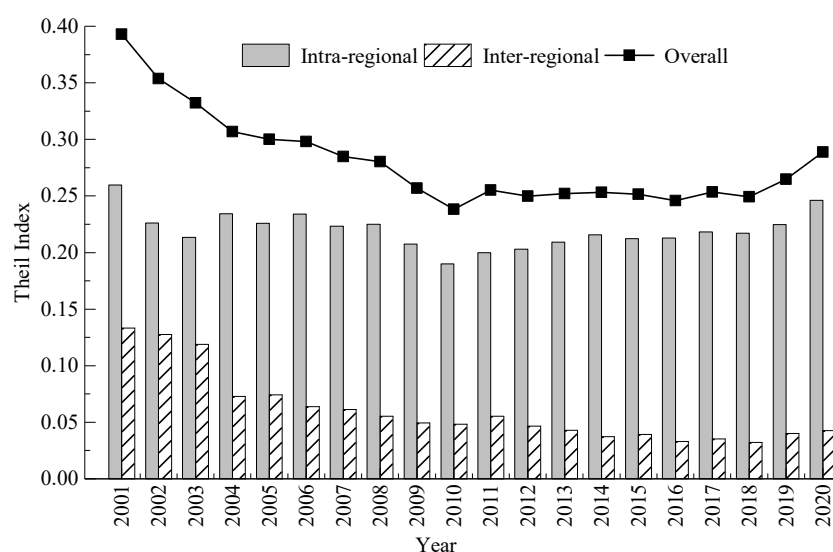


Figure 3. One-stage Theil index and its decomposition in Inner Mongolia from 2001 to 2020.

In the two-stage Theil nested index (Figure 4), the means of intra-league (city) disparities, inter-league (city) disparities, and inter-regional disparities are 0.14, 0.08, and 0.06, respectively. The findings for both the one-stage and two-stage Theil indices indicate that disparities in fertilizer application intensity are influenced by inter-regional differences. The contribution of these disparities predominantly stems from the intra-league (city) disparities. Further analysis reveals that intra-regional disparities are the main contributors to overall disparities. As shown in Figure 5, the disparities between the central, western, and eastern regions of Inner Mongolia overlap and contribute to the overall disparities. Eastern Inner Mongolia exhibits the highest contribution rate, with mean rates of 1.93%, 2.59%, and 3.73%, respectively.

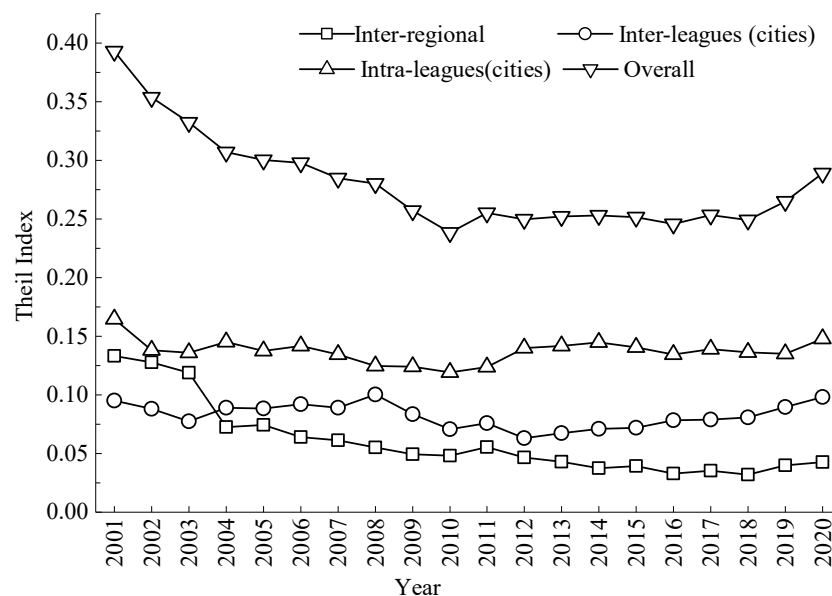


Figure 4. Two-stage nested Theil index and its decomposition from 2001 to 2020.

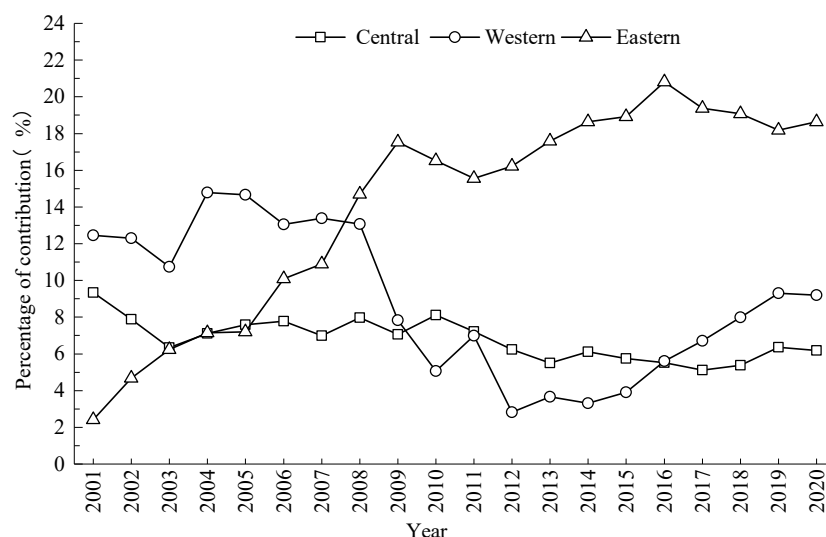


Figure 5. Contribution of intra-regional disparities to overall disparities from 2001 to 2020.

Table 2 depicts intra-league (city) and inter-league (city) disparities. In eastern Inner Mongolia, Chifeng has the highest disparities, with a mean difference of 0.24, while Tongliao has lower disparities than Chifeng, with a mean difference of 0.14. However, Tongliao has the highest contribution rate to the overall difference at 6.76%, indicating that Tongliao uses more fertilizer in a greater number of banners (counties). Conversely, Hinggan League has the smallest disparities and contribution rate, indicating a larger number of banners (counties) with lower fertilizer application intensity within Hinggan League. In central Inner Mongolia, Xilingol League exhibits significantly higher disparities than Hohhot and Ulanqab, with a mean difference of 0.46. This discrepancy mainly arises from the fact that nine out of the eleven banners (counties) in Xilingol League are situated in pastoral and semi-agricultural regions. There is a notable contrast in fertilizer use between agricultural and pastoral areas, leading to substantial overall disparities. Nonetheless, Hohhot surpasses Xilingol League in contribution rate, indicating more intense fertilizer application in Hohhot. This implies a more uneven distribution of fertilizer application intensity in Xilingol League. Ulanqab has the lowest disparities in both value and contribution rate, with mean values of 0.15 and 3.71%, respectively. In western Inner Mongolia, Baotou has the highest disparities

in value and contribution rate, at 0.12 and 5.11%, respectively. This indicates high, uneven fertilizer application intensity. The disparity value in Ordos exceeds that of Bayan Nur, at 0.12 and 0.10, respectively, but Ordos's contribution rate is lower than that of Bayan Nur, at 3.45% and 4.60%, respectively. This implies that the overall fertilizer application intensity in Bayan Nur is higher than in Ordos, and Ordos's fertilizer application intensity is more uneven than Bayan Nur's.

Table 2. Two-stage nested Theil index and contribution within each league (city).

District	Leagues (Cities)	2001		2004		2007		2010		2013		2016		2019		2020	
		Index	Contribution Rate	Index	Contribution Rate	Index	Contribution Rate	Index	Contribution Rate	Index	Contribution Rate	Index	Contribution Rate	Index	Contribution Rate	Index	Contribution Rate
East	Hulun Buir	0.145	2.127	0.185	3.579	0.121	2.669	0.141	3.526	0.151	3.594	0.155	3.947	0.137	3.068	0.146	2.907
	Hinggan League	0.058	0.602	0.033	0.486	0.067	1.496	0.028	0.71	0.03	0.72	0.082	2.219	0.061	1.262	0.058	1.121
	Tongliao	0.295	5.015	0.114	3.821	0.089	3.883	0.102	5.798	0.135	7.723	0.164	10.554	0.158	8.889	0.182	9.835
	Chifeng	0.228	5.826	0.238	8.480	0.16	6.326	0.084	4.218	0.119	5.516	0.139	6.991	0.151	6.78	0.152	5.928
Middle	Hohhot	0.334	9.447	0.24	8.022	0.283	9.042	0.233	8.872	0.181	6.506	0.149	5.585	0.148	5.538	0.175	5.991
	Xilingol League	0.238	1.809	0.354	4.550	0.512	6.081	0.452	6.621	0.579	9.982	0.551	10.195	0.563	10.072	0.575	8.96
	Ulanqab	0.221	3.009	0.24	5.434	0.177	4.263	0.163	5.28	0.153	4.352	0.108	3.076	0.096	2.261	0.1	2.137
West	Baotou	0.189	5.985	0.113	4.517	0.11	4.498	0.138	6.36	0.102	4.372	0.092	3.926	0.117	5.558	0.124	5.419
	Ordos	0.056	1.302	0.091	2.119	0.097	2.202	0.093	3.285	0.214	7.079	0.108	3.116	0.111	2.774	0.144	3.341
	Bayan Nur	0.079	2.861	0.091	3.867	0.115	5.075	0.101	5.131	0.125	5.821	0.107	4.908	0.104	4.226	0.119	4.726
	Wuhai	0.033	1.075	0.024	0.839	0.036	1.193	0.0003	0.008	0.007	0.171	0.003	0.071	0.011	0.321	0.02	0.536
	Alxa League	0.204	2.851	0.125	1.553	0.031	0.464	0.013	0.232	0.022	0.373	0.007	0.089	0.026	0.316	0.033	0.32

In summary, the use of fertilizers in Inner Mongolia has decreased over time. This trend can be attributed in part to recent policies such as the “Zero Growth Action Plan for Fertilizer Use by 2020”, “Proposal on Strengthening the Promotion of Organic Fertilizers”, and “National Sustainable Agricultural Development Plan (2015–2030)”, which have led to steady reductions in fertilizer application. Furthermore, this decline reveals the interplay and mutual influence among crop fertilizer application intensities. In addition, the Theil index calculation results indicate that disparities within regions are the main source of overall disparities. Therefore, policies aimed at reducing internal disparities within the regions can facilitate a decrease in fertilizer application intensity in Inner Mongolia. Spatial econometric models are used to explore the spatiotemporal heterogeneity of fertilizer application intensity drivers. This approach aims to fully grasp the characteristics of the spatiotemporal evolution and influencing factors of fertilizer application intensity, providing a basis for differentiated fertilizer reduction policies in Inner Mongolia.

3.2.2. Spatial Correlation Analysis

The Theil index is a statistical method that measures variability between data points, regardless of the effect of geographical location. Moran's I is used to explore how spatial distance and location affect fertilizer application intensity. First, we analyzed the global Moran's I to measure the spatial auto-correlation of fertilizer application intensity in Inner Mongolia from 2001 to 2020 (Table 3). The global Moran's I value is significant and positive, indicating a positive spatial correlation in fertilizer application intensity. This means that changes in fertilizer application intensity in one region are not independent and are influenced by various factors in neighboring regions. The next step was to examine the local Moran's I , which demonstrates the spatial clustering of fertilizer application intensity. The ensuing discussion delineates the clustering patterns of fertilizer application intensity in Inner Mongolia across different time periods (Figure 6).

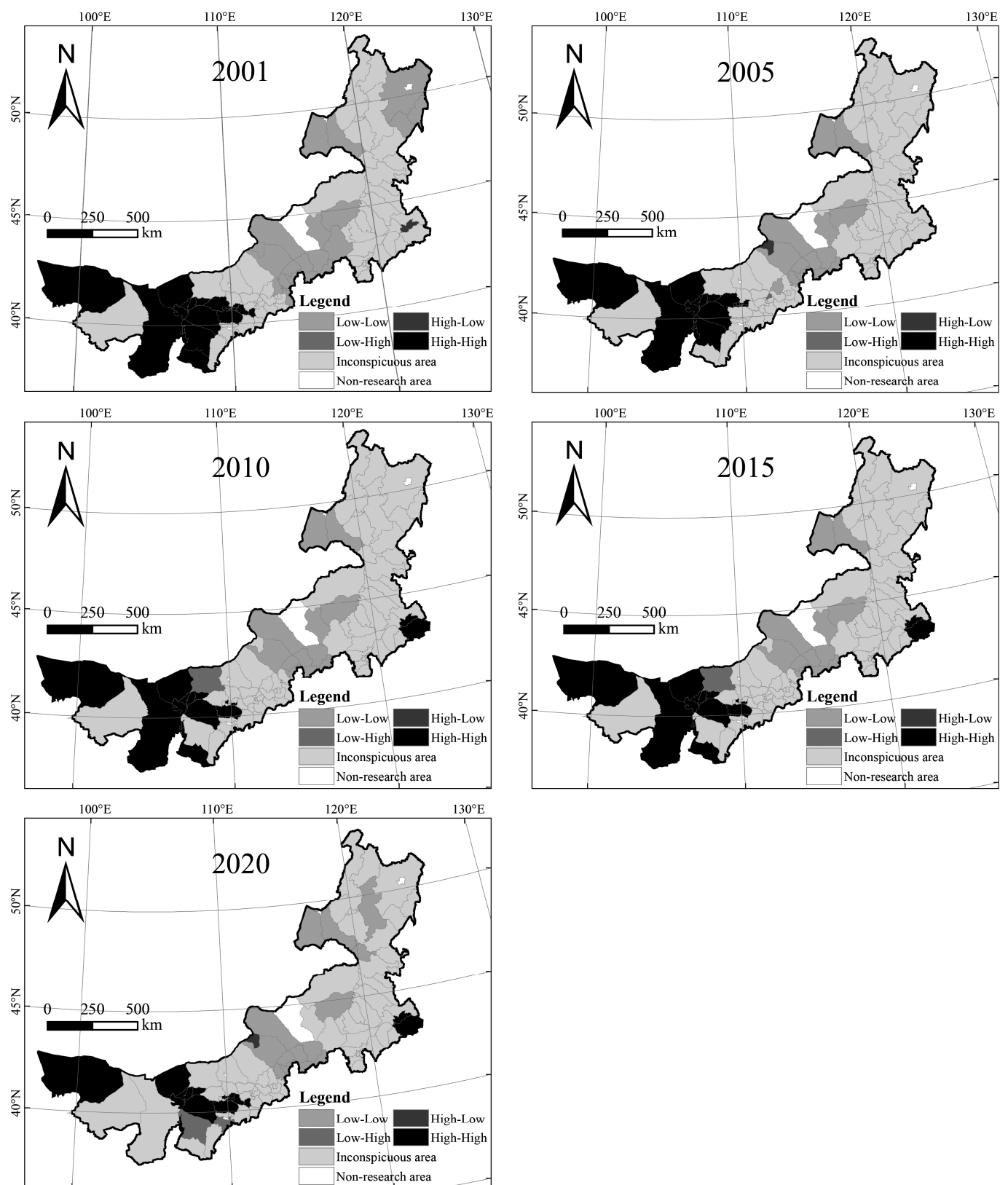


Figure 6. LISA cluster map of fertilizer application intensity in 2001, 2005, 2010, 2015, and 2020.

Table 3. Global Moran’s *I* values, 2001–2020.

Year	<i>I</i>	<i>Z</i>	<i>p</i> -Value	Year	<i>I</i>	<i>Z</i>	<i>p</i> -Value
2001	0.2376	10.494	0.000	2011	0.163	7.4055	0.000
2002	0.2287	10.124	0.000	2012	0.1439	6.6294	0.000
2003	0.2103	9.4256	0.000	2013	0.1488	6.8514	0.000
2004	0.1749	7.962	0.000	2014	0.1469	6.7362	0.000
2005	0.1792	8.1908	0.000	2015	0.1506	6.9185	0.000
2006	0.1666	7.6698	0.000	2016	0.1531	7.0225	0.000
2007	0.1598	7.3594	0.000	2017	0.1572	7.1664	0.000
2008	0.1645	7.5306	0.000	2018	0.1562	7.1292	0.000
2009	0.15	6.9238	0.000	2019	0.173	7.7946	0.000
2010	0.1517	6.9461	0.000	2020	0.174	7.8318	0.000

In 2001, fertilizer use intensity in Inner Mongolia already exhibited significant clustering characteristics. The low-low significant clustering areas were concentrated in the eastern region, including the New Barag Right Banner, New Barag Left Banner, Arong Banner, Roqen Autonomous Banner in Hulun Buir, and the surrounding areas of Sonid Left Banner, Sonid Right Banner, and East Ujimqin County in the central region of Xilingol League. Conversely, the high-high significant clustering areas were concentrated in the western region, including Wuhai, Ejina Banner, Alxa East County in Alxa League, Urad North County in Bayan Nur, and Otog Banner in Ordos, among other surrounding areas. In 2005, the low-low significant clustering area of Roqen Autonomous Banner transitioned into a low-low region, while Erenhot City, Otog Front Banner in Ordos, and Horqin Northeast Flag in Tongliao emerged as significant high-high clustering areas, and Urat Zhongqi in Bayan Nur became a significant low-high clustering area. In 2015, the significant clustering patterns of low-low and high-high areas remained largely unchanged. In 2020, the significant clustering of low-low areas continued to be concentrated in Xilingol League and Hulun Buir. Notably, Yakeshi City in Hulun Buir and West Ujimqin Banner in Xilingol League transitioned into low-low regions. Conversely, the significant clustering of high-high areas in the western region decreased significantly over time, shifting toward Tongliao and Chifeng, indicating a higher degree of chemical fertilizer application in the main grain-producing zones. Guo, Li, Xu, Sun, and Zhang [44] also identified an excessive use of fertilizers, resulting in a mere 40.2% fertilizer use rate for grain crops, while Otog Banner in Ordos became a significant high-low clustering area. Overall, the clustering pattern presented in the LISA map is generally consistent with the spatial distribution pattern of fertilizer application intensity in Inner Mongolia.

Over the past 20 years, the spatiotemporal patterns and regional significance of fertilizer application intensity in Inner Mongolia have undergone constant change. It is important to consider the spatial interaction characteristics of fertilizer application. Leveraging these spatial interaction characteristics can help enhance fertilizer use efficiency and reduce application intensity.

3.3. Analysis of Factors Affecting Fertilizer Application Intensity

3.3.1. Selection of Spatial Measurement Models

Moran’s *I* indicates that there is spatial dependence in the intensity of fertilizer application. Conventional econometric models neglect spatial aspects. In this study, we employed the Spatial Durbin Model to explore the determinants of fertilizer application intensity and its spatial spillover effects. The Spatial Durbin Model is a more general form that encompasses both the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), allowing for the simultaneous consideration of spatial lag and error effects in both the dependent and explanatory variables [45]. The study also conducted LM (Lagrange Multiplier) tests and LR (Likelihood Ratio) tests to validate the effectiveness of the SDM model (Tables 4 and 5). According to the LM test results (Table 4), both the lagged and error terms reject the null hypothesis of “no spatial autocorrelation”, leading to the preliminary selection of the Spatial Durbin Model (SDM). The LR test results (Table 5) show that the test statistics for the

SDM devolving into SAR and SEM are 113.24 and 119.15, respectively, rejecting the null hypothesis at the 1% significance level, indicating that the SDM does not degenerate into SAR or SEM. The Spatial Durbin Model also does not constrain potential spillover effects, enabling a more precise assessment of spatial spillover effects [46]. After confirming the effectiveness of the Durbin model, a Hausman test was conducted to determine whether to choose a fixed effects model or a random effects model. Table 5 indicates that the Hausman test rejects the null hypothesis of the “presence of random effects” at a 1% significance level, leading to the selection of a fixed effects model. Finally, the selection between time-fixed effects, individual fixed effects, and time–individual double-fixed effects is made, and regression is performed for the three types of fixed effects models. The results from Table 6 show that the R-squared value is highest for the time-fixed effects model, indicating the best fit, ultimately resulting in the selection of the time-fixed effects Durbin model.

Table 4. LM test results based on spatial measurement.

Test	Result
Moran’s <i>I</i>	18.201 ***
LM error	316.764 ***
R-LM error	0.016 *
LM lag	411.088 ***
R-LM lag	94.34 ***

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

Table 5. Hausman and LR test results based on spatial measurement.

Test	Fixed-Effects Model and Random Effects Model SDM	Whether SDM Is Degraded to SAR	Whether SDM Is Degraded to SEM
Method Result	Hausman test 60.38 ***	LR test 113.24 ***	LR test 119.15 ***

Note: *** indicate significance levels of 1%, respectively.

Table 6. Spatial Durbin model results.

	Time Fixed Effects	Individual Fixed Effects	Dual Time–Individual Fixed Effects
Main			
Ln LAB	−8.9995 ** (4.5032)	−11.1033 (7.9124)	−9.7085 (7.9534)
Ln AFFL	23.6249 *** (4.6750)	39.4930 *** (8.4262)	38.6983 *** (8.4330)
Ln MECH	10.8002 ** (5.4910)	20.6425 *** (4.6848)	21.4928 *** (4.6920)
Ln AEL	−4.3321 (4.3583)	19.0210*** (6.0115)	18.7975 *** (6.0047)
Ln GS	24.1801 *** (2.9388)	−13.2345 *** (4.2936)	−13.1681 *** (4.2857)
Ln LS	−39.5591 *** (5.0060)	7.1361 (6.5315)	8.7434 (6.5685)
Wx			
Ln LAB	24.9778 * (14.4978)	154.9800 *** (32.8945)	170.7401 *** (42.2364)
Ln AFFL	264.5944 *** (39.3365)	−27.4643 *** (9.7399)	−143.8929 ** (66.2643)
Ln MECH	−85.3963 *** (31.8877)	121.7590 *** (19.6057)	139.5851 *** (21.7655)
Ln AEL	87.3714 *** (22.4972)	61.4099 *** (14.1033)	55.1463 (35.8552)

Table 6. Cont.

	Time Fixed Effects	Individual Fixed Effects	Dual Time–Individual Fixed Effects
Ln GS	209.0802 *** (19.2693)	−27.8503 ** (12.5259)	−54.6113 *** (17.8764)
Ln LS	−177.1850 *** (29.5056)	33.2449 (23.7762)	62.2914 ** (28.6497)
Spatial rho	0.7068 *** (0.0483)	0.1049 (0.0801)	0.0797 (0.0817)
Variance sigma2_e	18,531.5149 *** (596.1328)	4399.3226 *** (139.8497)	4373.7049 *** (139.0440)
N	1980	1980	1980
R ²	0.4901	0.0157	0.0324
N	1980	1980	1980

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

3.3.2. Estimation Results and Analysis

LeSage argued that solving partial derivatives is a more accurate method [47]. Inspired by this approach, we utilized the Spatial Durbin Model (SDM) to examine the factors influencing fertilizer application intensity and their spatial spillover effects. We decomposed these effects into direct, indirect, and total effects for analysis, where the total effect is the sum of the direct and indirect effects (Table 7).

Table 7. Direct, indirect, and total effects of the time-fixed spatial Durbin model.

Variable	Direct	Indirect	Total
Ln LAB	−8.0548 * (4.1645)	63.2369 (45.5453)	55.1822 (43.7371)
Ln AFFL	36.9883 *** (5.2400)	937.6175 *** (191.0505)	974.6058 *** (193.8643)
Ln MECH	7.3257 (5.9147)	−270.0917 ** (115.2827)	−262.7661 ** (117.3884)
Ln AEL	−0.1918 (4.8320)	277.5733 *** (75.4296)	277.3815 *** (76.1897)
Ln GS	34.8942 *** (3.4829)	777.0334 *** (136.0019)	811.9276 *** (137.0755)
Ln LS	−49.1766 *** (5.8133)	−697.0708 *** (136.2410)	−746.2474 *** (137.8634)
R ²	0.4901	0.4901	0.4901
N	1980	1980	1980

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

Based on the results in Table 7, rural labor input has a significant negative direct effect on fertilizer application intensity, while the indirect and overall effects are positive but not statistically significant. The results suggest a relatively reasonable composition of the local effective labor force, favoring the rational application of fertilizer. However, some studies have shown that older generations have a strong emotional attachment to the land and a keen awareness of the need to conserve arable land, potentially leading to reduced fertilizer application [48]. The indirect effect suggests that an increase in rural laborers in adjacent areas can elevate fertilizer application intensity locally. Non-agricultural employment opportunities often increase the likelihood of substituting fertilizer for labor input [42]. Zhou et al., also found that non-local employment leads to a significant increase in fertilizer consumption. Compared to local employees, individuals returning to rural areas for agricultural production face higher opportunity costs, thus they are more likely to use fertilizer inputs as a substitute for labor input [49].

The direct, spillover, and total effects of the per capita net income of rural residents on fertilizer application intensity are all positive, with the spillover effect surpassing the direct effect, possibly owing to spillover effects induced by homogenized competition [47]. Xu et al., also found that an increase in farmers' income incentivizes them to increase fertilizer usage to attain higher profits [33]. This may also be attributed to non-agricultural employment providing farmers with additional income sources, making it easier for them to purchase fertilizer. As non-agricultural income gradually increases, farmers often reduce their attention to land management [50]. However, there exists an inverted U-shaped relationship between income and input of production factors [51], which means there is a turning point in the relationship. Once farmers' income reaches its peak, they no longer excessively fertilize for income purposes, and they begin to consider environmental issues for future generations. Our research findings indicate that the relationship between these two factors in Inner Mongolia has not yet reached the turning point of the inverted U-shaped pattern.

The direct effect of agricultural modernization levels on fertilizer application intensity is positive but not significant, while the indirect effect is negative and significant, with the latter far outweighing the former. The ongoing progression of agricultural mechanization is set to drive the continual diffusion of agricultural production technologies [52]. Concurrently, urbanization drives farmers to boost productivity and replace labor through the adoption of agricultural machinery [53]. Mechanized fertilization can reduce the inefficiencies and waste associated with manual fertilization [27]. Agricultural machinery is a typical labor-saving technology and the fastest way to improve agricultural production efficiency [7,54]. However, some studies indicate that significant investment in agricultural machinery may increase reliance on fertilizers [55]. The relationship between agricultural mechanization and fertilizer application intensity follows an inverted U-shaped pattern. Effective reduction in fertilizer application intensity occurs only when mechanization reaches a certain level [27]. The small-scale farming economy is a significant factor leading to high fertilizer use among Chinese farmers [56]. In small-scale farming, the pollution caused by the small machinery owned by most farmers can be mitigated by increasing the proportion of large-scale agricultural machinery, thereby reducing fertilizer inputs [57].

The change in the proportion of the agricultural economy has a negative but non-significant direct impact on fertilizer application intensity, while the indirect impact is positive and significant, with the spatial spillover effect far outweighing the direct effect. This finding is consistent with Li and Shang [58]. Although China has been promoting agricultural sustainability, the growth of the agricultural economy still relies on the consumption of production factors such as fertilizers. Due to differences in soil quality and terrain across regions, farmers inevitably adjust their fertilizer application to maintain yields. Further, the easy dispersal of fertilizers can result in spatial spillover between regions. Additionally, the introduction of fertilizer reduction measures such as slow-release fertilizers, soil testing-based fertilization, and organic fertilizer substitution has partially controlled fertilizer usage. However, due to the high costs associated with these fertilizer reduction technologies, the extent of fertilizer reduction remains limited [59,60]. Based on our research findings, reducing the spillover effects of neighboring agricultural economies can effectively adjust fertilizer application intensity in the local area.

The effects of grain production on fertilizer application intensity, whether direct, indirect, or total, are all significant and positive. This indicates that grain production is a significant driving force behind fertilizer application intensity. When production increases, farmers are more inclined to use more fertilizer to achieve higher yields, and the imitation effect on the surrounding areas is more significant. Therefore, greater emphasis should be placed on scientific fertilization practices to maximize their socioeconomic benefits. This outcome also indicates that the farmers' disposition to "apply more for higher yields" still prevails, which presents a major obstacle to reducing fertilizer use and addressing non-point source pollution issues.

The direct, indirect, and total effects of arable land area on fertilizer application intensity are all negative and significant. The potential reasons are as follows: On the one hand, the accelerated urbanization process will further reduce arable land area, thereby limiting the increase in fertilizer usage [8]. On the other hand, moderate-scale arable land not only reduces local fertilizer application intensity but also radiates to drive neighboring areas towards large-scale operations. This increase necessitates investment in mechanical facilities, enhancing fertilizer efficiency. Hu et al., [29] also discovered that larger farm sizes are associated with higher fertilizer usage rates. Larger land sizes imply stronger bargaining power for farmers in the market, prompting them to reduce fertilizer usage and enhance crop quality due to shifts in identity and values. Larger land sizes also prompt farmers to demand higher levels of social services, and higher levels of services adjust fertilizer application by selecting premium fertilizers or using more reasonable fertilization methods [33]. Intensive farming is one way to ensure food security. However, studies have shown that over the past 20 years, land rents and agricultural labor wages have increased by more than 300%, while fertilizer prices have only risen by 35% [61]. The intensive cost of land far surpasses the cost of fertilizer application, making farmers more inclined to increase fertilizer usage.

4. Discussion

4.1. Interpretation of the Dynamics of Fertilizer Application Intensity

The excessive application of fertilizers poses significant hazards to the land and environment. The issue of reducing chemical fertilizer usage has garnered attention and importance from various sectors of society. It is generally believed that non-point source pollution issues such as soil compaction, water eutrophication, and heavy metal contamination caused by excessive fertilizer application are primarily due to the prolonged overuse of fertilizers, incomplete nutrient absorption by crops, and the runoff of excess fertilizers into lakes and rivers through rainfall, resulting in non-point source pollution. This study's findings reveal that fertilizer application intensity in Inner Mongolia surpassed the global average during the research period, presenting serious challenges to both the sustainability of agricultural development and national food security. Hence, the prudent application of fertilizers guided by scientific principles emerges as the central focus for fostering the healthful progression of agriculture.

In the context of rapid agricultural economic growth, China's grain production is gradually relocating to northern regions [15], with Inner Mongolia being one of its 13 major grain-producing regions, holding a crucial position in the national grain supply. This study's analysis of fertilizer application intensity classification reveals that the western and eastern regions of Inner Mongolia exhibit higher fertilizer application intensities. Moreover, areas with high and excessively high fertilizer application intensities are shifting towards the eastern region of Inner Mongolia (a key grain production base). This phenomenon suggests that farmers are adopting measures to increase fertilizer application to ensure yields, which, in turn, imposes pressure on the environment. In practical terms, these regions, which bear the responsibility for national food security, will inevitably increase fertilizer application. Effective policy measures can be inferred to enhance fertilizer utilization rates, thereby playing a role in addressing environmental sustainability issues.

In addition, this study found that rural labor force size, affluence level, grain yield, and arable land area have significant direct effects on fertilizer application intensity. In other words, as the labor force increases and attains higher qualifications, and when farmers' income reaches a certain threshold, there is a decrease in fertilizer application intensity. However, a greater proportion of non-agricultural income within the total income indicates a higher likelihood of increased fertilizer usage [7]. The economic level has multifaceted effects on the input of production factors. Non-agricultural employment influences the agricultural labor force, thereby leading to an increase in fertilizer application intensity. Agricultural mechanization serves as a means to mitigate this influence to a certain extent [62]. Furthermore, research indicates that households with an abundant labor

force tend to prioritize non-agricultural employment, leading to an increase in fertilizer usage [63]. The persistent rise in grain production serves as an incentive for farmers to further intensify fertilizer application, resulting in diminishing marginal returns [64]. This phenomenon results in decreased fertilizer application intensity as farms expand, with larger agricultural operations being more inclined to adopt advanced technologies in lieu of excessive fertilizer use [27]. In practice, controlling excessive fertilizer application can be achieved by adjusting these factors, though regional differences should be taken into account.

4.2. Mechanisms Driving the Evolution of Fertilizer Application Intensity

According to the impact mechanism and the calculation results of Moran's Index, it is evident that fertilizer application intensity in Inner Mongolia displays spatial correlation. To analyze the influencing factors and spatial effects of fertilizer application intensity, the Spatial Durbin Model (SDM) is utilized in this study. The findings reveal significant spatial spillover effects of prosperity level, modernization level, agricultural economic proportion, grain production, and arable land scale on fertilizer application intensity. This indicates that these factors not only influence the local area but also have an impact on the fertilizer application intensity in adjacent regions. The spillover effect of prosperity level on fertilizer application intensity exceeds its direct influence. Economic disparities exist among the leagues (cities) in Inner Mongolia. In comparison to economically affluent leagues (cities), those with lower economic statuses tend to hasten their development through imitation, resulting in homogeneous competition. The spillover effect demonstrated by the level of modernization is particularly pronounced. In certain regions, agricultural mechanization significantly stimulates fertilizer application intensity, while concurrently reducing it in neighboring areas. This phenomenon is closely tied to China's pursuit of agricultural modernization. With substantial investments in this endeavor, there is a significant deployment of agricultural machinery, which exhibits a notable dependency on fertilizers. However, with increasing mechanization and standardization of agricultural practices, reliance on fertilizers gradually diminishes [55]. The findings of this study suggest that large-scale land management plays a role in reducing fertilizer application intensity both locally and in neighboring areas. Large-scale land management facilitates the operation of large agricultural machinery, thereby reducing fertilizer application intensity and minimizing cost inputs [27,56].

4.3. Policy Implications

Firstly, it is recommended to accelerate the promotion of efficient fertilization techniques. The ongoing shift of agricultural labor to non-agricultural industries is an inevitable long-term trend. Research outcomes indicate that rural labor can significantly decrease fertilizer application intensity. Therefore, to prevent the potential rise in fertilizer application due to labor scarcity, governments need to strategically choose location-specific techniques for fertilizer reduction and efficiency enhancement. This involves enhancing the dissemination and implementation of technologies such as precision fertilization, deep tillage fertilization, soil testing-based fertilization, and integrated water and fertilizer management.

Secondly, it is important to recognize the geographical disparities in fertilization intensity and exploit spatial interaction effects. On the one hand, research findings indicate significant intra-regional variations in fertilizer application intensity in Inner Mongolia. Therefore, tailored fertilizer reduction measures should be implemented based on the level of agricultural economic development, soil quality, and cropping pattern characteristics within each league (city). Additionally, utilizing spatial spillover effects, the interactive influence and driving force of leagues (cities) with lower fertilizer application intensity can be harnessed to narrow regional disparities and reduce overall fertilizer application intensity. On the other hand, it is important to efficiently utilize the spatial spillover effects brought about by the degree of agricultural modernization. The agricultural machinery input from surrounding areas can exert a strong radiating effect on reducing fertilizer ap-

plication intensity in the local region. Thus, governments should formulate comprehensive and coordinated agricultural resource utilization policies to guide mutual influence and driving forces among adjacent regions, avoiding overly unilateral policies that neglect certain aspects.

Thirdly, empirical evidence suggests that the expansion of arable land area has a significant impact on reducing fertilizer application intensity. Hence, expediting land transfer and establishing relatively intensive operation scales through the clarification of permanent land transfer rights can facilitate the dissemination of scientific fertilization techniques. This involves standardizing farmers' fertilization practices to lower fertilizer application intensity. Additionally, moderately scaled operations can enhance farmers' resilience to risks, thereby mitigating the tendency to increase fertilizer application to safeguard yields based on experiential risk predictions. In addition, optimizing agricultural layout by planning layouts conducive to forming integrated planting and animal husbandry cycles can optimize resource allocation and foster circular agriculture, thus reducing fertilizer application intensity and ensuring food security.

4.4. Future Research

This study delves into the intensity of fertilizer application in agricultural production, using Inner Mongolia as a case study. It contributes to the understanding of current levels of fertilizer application intensity in agriculture for relevant departments and government bodies. Additionally, the study explores the regional disparities and spatial spillover effects of fertilizer application intensity across different flags (counties) in Inner Mongolia. Consequently, the research findings can serve as a reference for the formulation of policies aimed at improving fertilizer utilization rates in Chinese agriculture, from the perspective of regional coordination and linkage. Moreover, the research framework of this study is not only applicable to analyzing agriculture in China but also extends to the analysis of other industries and countries. In examining the factors influencing fertilizer application intensity, this paper discusses the spatial correlation between influencing factors and fertilizer application intensity. Factors such as prosperity level, modernization level, proportion of agricultural economy, and agricultural scale not only affect fertilizer application intensity in the local area but also have a significant impact on neighboring regions. Therefore, this paper not only analyzes the factors influencing fertilizer application intensity in the local area but also explores the spatial spillover effects of fertilizer application intensity using the Spatial Durbin Model (SDM).

In addition, with the development of China's social and economic landscape and the evolution of agricultural production methods, it is anticipated that there will be more noticeable changes in agricultural fertilization intensity. This study has certain limitations. For instance, different crops require different nutrients for growth. The paper only discusses the total amount of fertilizer application in a region, without examining the spatial differences in fertilizer application intensity under different types of fertilizers or fertilizer ratios, and their impacts on the environment. The primary research focus of this study is Inner Mongolia. In the future, similar research needs to be conducted in different regions and agricultural environments, including further comparative analyses between plains and hills, as well as between grain-producing and non-grain-producing regions.

5. Conclusions

This study calculates fertilizer application intensity in 99 leagues (cities) in Inner Mongolia from 2001 to 2020 and uses the Theil index and Moran's I to test the spatial heterogeneity and correlation of fertilizer application intensity. Further, the Durbin model is applied to clarify the spatial spillover effects of fertilizer application intensity. The main conclusions are as follows: (1) In Inner Mongolia, the distribution of fertilizer application intensity shows a basic trend where the central region, with low-intensity application, acts as the epicenter, gradually strengthening towards both the western and eastern regions and transitioning gradually from the western to the eastern regions. Overall disparities

in fertilizer application intensity are decreasing, with intra-regional disparities being the main source of this difference. Further analysis of the intra-regional disparities reveals that the disparities stem from intra-league (city) disparities, with the highest contribution rate observed in the eastern region. (2) Fertilizer application intensity exhibits significant positive spatial correlations, mainly characterized by “high-high” and “low-low” clustering types. The significant “high-high” clustering is prominently distributed in the western region of Inner Mongolia, gradually transitioning to areas such as Tongliao City and Chifeng City in the eastern region. “Low-low” clustering is prominently distributed in the eastern and central regions, with Xilin Gol League in the central region showing the most significant clustering. Future endeavors to decrease fertilizer application intensity are mainly focused on establishing “high-high” clusters. (3) Farmers’ affluence, the proportion of the agricultural economy, and grain yield significantly drive agricultural fertilizer application intensity. Moreover, farmers’ affluence, the level of agricultural modernization, the proportion of the agricultural economy, and agricultural scale exhibit significant spatial spillover effects. In the future, policymakers can formulate more targeted regional fertilizer reduction policies based on the agglomeration characteristics of fertilizers. Simultaneously, they can mitigate the intensity of fertilizer application between regions by adjusting the spatial interaction of these factors, thereby alleviating the environmental harm caused by excessive fertilizer usage.

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