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Original Research

Gradient of New Quality Productive Forces and Pesticide Application Intensity of Grain Crops: Distribution Evolution, Sources of Differences, and State Lock-In

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Abstract

This study examines the spatiotemporal evolution, regional disparities, state transitions, and driving factors of pesticide use intensity in China's grain crops from 2005 to 2023. Using provincial panel data, pesticide use in grain crops was estimated by an area-proportional allocation method, and pesticide use intensity was measured as pesticide input per unit of grain output. Using agricultural new-quality productive forces (NQP) as a regional stratification framework, provinces were grouped into low-, medium-, and high-level regions. Kernel density estimation, GE0 decomposition, Markov chain analysis, and LMDI decomposition were employed to investigate distributional evolution, disparity sources, transition characteristics, and driving mechanisms. The results show that pesticide use intensity declined in all three regional types, with the low-, medium-, and high-level regions decreasing from 1.71, 1.77, and 2.75 kg/t in 2005 to 1.16, 1.07, and 1.72 kg/t in 2023, respectively; the high-level region recorded the largest reduction (1.03 kg/t). Kernel density curves generally shifted leftward and became more concentrated, indicating an overall decline and partial convergence, although a persistent right tail suggests that some high-intensity provinces remained. The GE0 index rose from 0.216 in 2005 to a peak of 0.283 in 2013 and then declined to 0.248 in 2023, while intra-regional disparities consistently dominated overall inequality, accounting for 86.1% in 2005 and 88.7% in 2023. Markov results show strong state persistence, with no direct transitions between low- and high-intensity states. LMDI results indicate that the sharpest decline occurred during 2016-2020, mainly driven by the negative shift in the total pesticide use effect, while grain output continued to exert a downward influence. These findings suggest that pesticide reduction in China's grain sector is characterized by gradual adjustment, strong within-group heterogeneity, and differentiated regional pathways and therefore requires more targeted governance strategies that balance food security with green agricultural development.

Keywords: grain crops, pesticide use intensity, spatiotemporal evolution, regional disparity, new quality productive forces

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Introduction

Chemical pesticides have long been central to stabilizing crop yields and safeguarding the food supply, but their intensive use also generates substantial environmental costs, including soil and water contamination, ecological degradation, and long-run sustainability risks in agricultural systems [1, 2]. Global-scale assessment further shows that approximately 64% of agricultural land is exposed to pesticide pollution risk and 31% is at high risk, indicating that pesticide governance is not merely a farm-management issue but also a major spatial environmental challenge [3]. For China, this issue is especially salient because grain production must simultaneously achieve the dual objectives of food security and green transformation, while past reliance on chemical inputs has already triggered broad concern over agricultural non-point source pollution and input overuse [1]. In response, China launched the "zero growth" action for chemical fertilizer and pesticide use in 2015, marking a shift from output-oriented expansion toward resource-saving and environmentally constrained agricultural development [4]. Against this background, identifying how pesticide use intensity in grain crops evolves across space and time, and clarifying the sources of regional differences, has become a question of both academic and policy relevance.

Existing studies have made important progress in at least three directions. First, a growing body of work has examined the temporal dynamics of pesticide use and the effects of reduction policies, showing that chemical-input trajectories are shaped jointly by regulatory intervention, production incentives, and technological change [4]. Second, spatial studies have documented pronounced regional differentiation in fertilizer and pesticide use, and have shown that local production conditions, development patterns, and management practices influence the level and evolution of agricultural chemical inputs [5]. Third, broader sustainable agriculture research increasingly emphasizes that pest management should be studied together with technological transition and ecological governance: a recent global synthesis suggests that a transformation toward sustainable pest management could generate broad benefits for productivity, environmental sustainability, and human well-being, but that these gains are highly heterogeneous across regions and indicators [6]. Related work on climate-smart technology adoption likewise shows that innovation-oriented production strategies can improve both agricultural productivity and environmental sustainability [7]. In parallel, research on one-time application of biochar and compost demonstrates that greener input strategies may produce cumulative agronomic and soil benefits over multiple consecutive cropping cycles, while bibliometric evidence on agricultural waste-based bioplastics highlights the growing importance of circular, bio-based material systems in the broader transition of agricultural inputs [8]. Taken together, these studies suggest that pesticide reduction should not be viewed as an isolated issue of chemical control, but as part of a wider transformation in agricultural production technology, resource allocation, and green governance [6].

Nevertheless, two limitations remain in the existing literature. One is that many regional comparisons still rely on conventional stratification schemes such as administrative divisions, broad macro-regions, or major-versus-non-major production areas, which are useful for descriptive comparison but are less effective in capturing differences in technological upgrading, factor reorganization, and green transformation capacity across production systems [5]. The other is that many studies either focus on aggregate agricultural chemical use or emphasize outcome-oriented indicators such as green production efficiency, rather than examining pesticide use intensity per unit of grain output under a development-stage-based regional framework [9]. This gap matters because grain-crop pesticide use intensity is shaped not only by the amount of pesticide applied, but also by crop structure, production organization, technology adoption, and the ecological conditions under which output is generated [6]. In other fields of environmental geography, recent work on carbon budget and balance zoning has shown that combining spatial differentiation analysis with functional zoning can reveal hidden heterogeneity and support more targeted regional governance [10]. This insight is highly relevant here, because pesticide-use governance likewise requires more refined regional identification than can be provided by coarse administrative grouping alone.

It is in this context that this study introduces new-quality productive forces (NQP) as a stratification perspective. In the agricultural field, recent studies describe NQP as an innovation-driven development configuration characterized by technological upgrading, reorganization of production factors, digital–green integration, and stronger coordination between productivity improvement and ecological objectives [11]. In this sense, NQP is related to, but not identical with, agricultural modernization or agricultural green production efficiency. Agricultural modernization usually emphasizes structural upgrading and development outcomes, whereas green production efficiency is an outcome indicator evaluating input–output performance under environmental constraints; by contrast, NQP refers more fundamentally to the capability base and transformation logic that make such outcomes possible, especially through innovation, intelligent production tools, and ecological restructuring [12]. Therefore, compared with traditional grouping methods based only on geography, resource endowment, or single performance indicators, NQP-based regional stratification is better suited to identifying whether differences in pesticide use intensity reflect deeper differences in development stage, technological capacity, and green transition potential.

Based on this logic, the present study examines the spatiotemporal evolution, regional disparities, state transitions, and driving-factor decomposition of pesticide use intensity in China's grain crops from 2005 to 2023 under an NQP-based regional stratification framework. Specifically, this study seeks to answer four questions: whether pesticide use intensity in grain crops exhibits stage-specific spatiotemporal evolution; whether regional disparities are driven primarily by inter-regional gaps or by within-region heterogeneity; whether the observed decline in pesticide use intensity is accompanied by strong path dependence and state stickiness; and which factors drive changes in pesticide use intensity across stages and regional types. By addressing these questions, this study aims not only to enrich the literature on agricultural chemical-use transition, but also to provide a more development-sensitive basis for differentiated pesticide-reduction policy in major grain-producing systems.

Materials and Methods

Data Sources

This study uses panel data for 31 provincial-level regions in mainland China from 2005 to 2023, excluding Hong Kong, Macao, and Taiwan due to data discontinuity and differences in statistical standards. The original data on total agricultural pesticide use, total cultivated land area, grain-crop cultivated area, and grain output were mainly collected from the China Statistical Yearbook and the China Rural Statistical Yearbook for the corresponding years. The regional stratification variable, namely the agricultural new-quality productive forces level (NQP level), was not newly constructed in this study. Instead, it was obtained with reference to relevant literature and then averaged over 2005-2023 to classify provinces into low-, medium-, and high-level regions. In this study, the NQP level is used primarily as a long-run regional stratification criterion rather than as a causal explanatory variable.

To improve readability, the empirical analysis is organized into four steps. First, pesticide use intensity in grain crops is estimated at the provincial level. Second, kernel density estimation and GE0 decomposition are used to characterize distributional evolution and disparity sources. Third, the Markov chain method is employed to identify state transitions and path dependence. Fourth, the Logarithmic Mean Divisia Index (LMDI) method is applied to decompose the driving forces of changes in pesticide use intensity.

Measurement of Pesticide Use Intensity in Grain Crops

To characterize the level of pesticide input per unit of output in grain production, this study constructs an indicator of pesticide use intensity in grain crops, defined as pesticide input per unit of grain output. Since official yearbooks report only total agricultural pesticide use at the provincial level, while crop-specific provincial pesticide-use data are unavailable, this study adopts an area-proportional allocation method to estimate pesticide use attributable to grain crops [13].

Let P_{it} denote total agricultural pesticide use in province i in year t, A_{it} denote total cultivated land area, G_{it} denote grain-crop cultivated area, and Q_{it} denote grain output. The estimated pesticide use for grain crops, P_{it}^{g}, is calculated as:

$$P_{it}^{g} = P_{it} \times \frac{G_{it}}{A_{it}} \quad (1)$$

Pesticide use intensity in grain crops, I_{it}, is then defined as pesticide use per unit of grain output:

$$I_{it} = \frac{P_{it}^{g}}{Q_{it}} \quad (2)$$

Substituting Eq. (1) into Eq. (2), the actual estimation formula can be written as:

$$I_{it} = \frac{P_{it} \times G_{it}}{A_{it} \times Q_{it}} \quad (3)$$

If P_{it} and Q_{it} are both measured in tonnes, the unit of I_{it} is t/t. To improve interpretability, this study converts it into kg/t as follows:

$$I_{it}^{*} = 1000 \times \frac{P_{it} \times G_{it}}{A_{it} \times Q_{it}} \quad (4)$$

A larger value of this indicator indicates higher pesticide use intensity per unit of grain output, whereas a smaller value indicates relatively lower pesticide input under a given output level.

It should be noted that the area-proportional allocation method inevitably introduces estimation uncertainty. It assumes that the grain-crop share of pesticide use is proportional to the grain-crop share of cultivated land. Therefore, the estimated value should be interpreted as a comparative proxy for interprovincial and temporal analysis, rather than as a direct observation of crop-specific pesticide application behavior.

Kernel Density Estimation

To depict the distributional evolution of pesticide use intensity in grain crops, this study employs kernel density estimation (KDE). Compared with conventional descriptive statistics, KDE can more intuitively reveal changes in distribution location, dispersion, peakedness, and tail behavior [14].

Suppose that in a given year there are n provinces in the sample, and the observed values of pesticide use intensity in grain crops are x_1, x_2, ..., x_n. The kernel density estimator can be expressed as:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{5}$$

where $\hat{f}(x)$ is the estimated kernel density at point x, $K(\cdot)$ is the kernel function, and h is the bandwidth parameter.

This study adopts the Gaussian kernel function:

$$K(u) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{u^2}{2}\right) \tag{6}$$

Because pesticide use intensity is a non-negative variable, attention is paid to possible boundary effects near zero when interpreting low-value concentrations. KDE is used here mainly to identify whether the distribution shifts leftward or rightward over time, whether it becomes more concentrated or more dispersed, and whether a persistent right tail remains.

GE0 Index and Regional Decomposition

To quantify interprovincial disparities and identify their sources, this study employs the GE0 index in the generalized entropy family [15]. Let I_{it} denote pesticide use intensity in grain crops of province i in year t, and let $\bar{I}_t$ denote the national mean in year t. The GE0 index is defined as:

$$GE0_t = \frac{1}{N}\sum_{i=1}^{N} \ln\left(\frac{\bar{I}_t}{I_{it}}\right) \tag{7}$$

A larger $GE0_t$ indicates greater interprovincial disparity, whereas a smaller value indicates a more balanced distribution.

Suppose there are R regional groups and let N_r denote the number of provinces in region r, while $\bar{I}_{rt}$ denotes the mean pesticide use intensity of region r in year t. Then the overall disparity can be decomposed into inter-regional and intra-regional components:

$$GE0_t = GE0_t^B + GE0_t^W \tag{8}$$

The inter-regional component is:

$$GE0_t^B = \sum_{g=1}^{G} \frac{N_{g,t}}{N_t}\ln\left(\frac{\bar{I}_t}{\bar{I}_{g,t}}\right) \tag{9}$$

The intra-regional component is:

$$GE0_t^W = \sum_{g=1}^{G} \frac{N_{g,t}}{N_t} GE0_{g,t} \tag{10}$$

where the within-region GE0 index is:

$$GE0_{g,t} = \frac{1}{N_{g,t}}\sum_{i \in g} \ln\left(\frac{\bar{I}_{g,t}}{I_{it}}\right) \tag{11}$$

This decomposition allows the study to determine whether overall disparity is driven mainly by differences across NQP-based regional groups or by heterogeneity within groups.

Markov Chain Method

To further examine the dynamic evolution of pesticide use intensity in grain crops, this study uses the Markov chain method [16]. Based on the interprovincial cross-sectional distribution in each year, provinces are classified into three states using tertile thresholds: low-intensity, medium-intensity, and high-intensity.

Let p_{ij} denote the probability that a province moves from state i in period t to state j in period $t + 1$. The Markov transition probability matrix is:

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \tag{12}$$

with the row-sum condition:

$$\sum_{j=1}^{m} p_{ij} = 1 (i = 1,2, \ldots, m) \tag{13}$$

In empirical calculation, transition probabilities are obtained by row-normalizing the frequencies of observed state transitions. Let n_{ij} denote the number of transitions from state i to state j. Then:

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^{m} n_{ij}} \tag{14}$$

To assist long-run interpretation, the stationary distribution vector π is also considered satisfying:

$$\pi = \pi P, \sum_{j=1}^{3} \pi_j = 1 \tag{15}$$

The Markov framework is used here mainly to identify state persistence, adjacent transitions, and path dependence in the evolution of pesticide use intensity.

LMDI Model

To identify the sources of changes in pesticide use intensity, this study adopts the additive LMDI method [17]. Based on the accounting identity of pesticide use intensity, the indicator can be expressed as:

$$I = \frac{P \times G \times 1000}{A \times Q} \tag{16}$$

where I denotes pesticide use intensity in grain crops, P denotes total agricultural pesticide use, G denotes grain-crop cultivated area, A denotes total cultivated land area, and Q denotes grain output.

Suppose the pesticide use intensity in the base period is I^0 and that in the reporting period is I^T. Then the total change is:

$$\Delta I = I^T - I^0 \tag{17}$$

Using the additive LMDI approach, ΔI can be decomposed as:

$$\Delta I = \Delta I_P + \Delta I_G + \Delta I_A + \Delta I_Q \tag{18}$$

where ΔI_p denotes the total pesticide use effect, ΔI_G denotes the grain-crop cultivated area effect, ΔI_A denotes the total cultivated land area effect, and ΔI_Q denotes the grain output effect.

Let $L(I^T, I^0)$ denote the logarithmic mean of I^T and I^0:

$$L(I^T, I^0) = \frac{I^T - I^0}{\ln I^T - \ln I^0} (I^T \neq I^0) \tag{19}$$

Then the four additive decomposition effects are expressed as:

$$\Delta I_P = L(I^T, I^0) \ln\left(\frac{P^T}{P^0}\right) \tag{20}$$

$$\Delta I_G = L(I^T, I^0) \ln\left(\frac{G^T}{G^0}\right) \tag{21}$$

$$\Delta I_A = L(I^T, I^0) \ln\left(\frac{A^0}{A^T}\right) \tag{22}$$

$$\Delta I_Q = L(I^T, I^0) \ln\left(\frac{Q^0}{Q^T}\right) \tag{23}$$

In Eqs. (22) and (23), the base-period term is placed in the numerator and the reporting-period term in the denominator to reflect the inverse effects of total cultivated land area and grain output, which appear in the denominator of the intensity indicator. A negative decomposition effect indicates that changes in the corresponding factor contribute to a decline in pesticide use intensity, whereas a positive effect indicates that the factor increases the intensity or offsets its decline.

Study Area Division

To examine regional heterogeneity under different development stages, the 31 provincial-level regions were classified into low-, medium-, and high-level regions according to the average NQP level over 2005–2023. The low-level region includes Tibet, Qinghai, Ningxia, Tianjin, Shanxi, Beijing, Gansu, Hainan, Chongqing, Inner Mongolia, and Xinjiang; the medium-level region includes Jilin, Guizhou, Shanghai, Shaanxi, Liaoning, Yunnan, Jiangxi, Guangxi, Anhui, and Heilongjiang; and the high-level region includes Hebei, Hubei, Hunan, Fujian, Henan, Zhejiang, Sichuan, Jiangsu, Shandong, and Guangdong. All subsequent analyses of distributional evolution, disparity decomposition, state transitions, and driver decomposition are conducted based on this grouping scheme.

Methodological Considerations

Two methodological issues should be noted. First, the pesticide use intensity indicator used in this study is a quantity-based measure and does not distinguish pesticide types, toxicities, or exposure risks. Therefore, it reflects production-linked pesticide dependence rather than a full risk-weighted environmental burden. Second, the province-level framework is suitable for long-run national comparison, but it may mask intra-provincial heterogeneity. Thus, the present analysis is more appropriate for identifying national and interprovincial patterns than for revealing local-scale variation within provinces.

Results

Regional Evolution Characteristics of Pesticide Use Intensity in Grain Crops

Fig. 1 shows clear regional heterogeneity in pesticide use intensity in grain crops over 2005–2023. Throughout the study period, the high-level region consistently recorded the highest intensity values, whereas the low- and medium-level regions remained relatively close to each other. In 2005, pesticide use intensity was 1.71 kg/t in the low-level region, 1.77 kg/t in the medium-level region, and 2.75 kg/t in the high-level region. By 2023, these values had declined to 1.16 kg/t, 1.07 kg/t, and 1.72 kg/t, respectively, indicating an overall downward trend across all three regional types.

In terms of stage-specific evolution, the low-level region first increased and then decreased. Its intensity rose from 1.71 kg/t in 2005 to 2.67 kg/t in 2011, remained relatively high during 2009–2013, and then entered a clear declining phase, especially after 2017. The medium-level region showed a comparatively moderate trajectory: it rose to 2.05 kg/t in 2010 and then gradually declined to 1.07 kg/t in 2023, the lowest among the three regional types. By contrast, the high-level region exhibited high-level fluctuations followed by a sustained decline. It remained within a relatively high range during 2006-2014, peaked at 3.01 kg/t in 2010, and then declined continuously after 2015, reaching 1.72 kg/t in 2023.

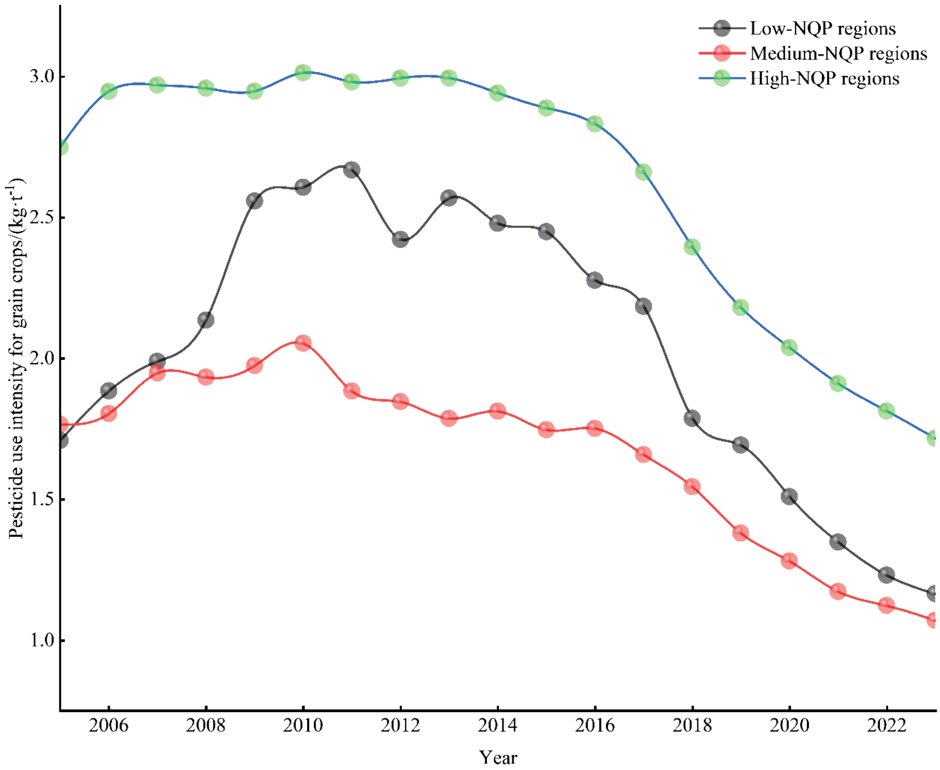

Fig. 1. Changes in pesticide use intensity in grain crops across the three regions.

From the perspective of total change, pesticide use intensity decreased by 0.54 kg/t, 0.70 kg/t, and 1.03 kg/t in the low-, medium-, and high-level regions, respectively, during 2005-2023. The largest reduction occurred in the high-level region, suggesting that regions with initially high pesticide dependence underwent more pronounced adjustment in the later period. Overall, all three regional types entered a clearer downward trajectory around or shortly after 2015, indicating a certain degree of synchronicity in the reduction process.

Distributional Evolution Characteristics of Pesticide Use Intensity in Grain Crops

The kernel density results indicate that the distribution of pesticide use intensity in grain crops generally shifted leftward over time, accompanied by increasing peak height and narrowing dispersion, which together suggest an overall decline in intensity and partial convergence across provinces. However, the right tail did not disappear completely, implying that a small number of high-intensity provinces remained by the end of the study period.

In the low-level region, the kernel density curves exhibited relatively strong fluctuations and a pronounced right-tail feature in the early period, indicating substantial intra-regional heterogeneity. After 2015, the distribution shifted leftward and became more concentrated, especially in 2020 and 2023, suggesting both declining intensity and some convergence within the region. The medium-level region showed a smoother pattern, characterized by an initial rightward shift followed by a marked leftward shift. By 2023, its peak was higher and narrower than in earlier years, indicating that the region experienced not only lower pesticide use intensity but also a more concentrated interprovincial distribution.

The high-level region displayed a persistently high-value distribution in the early sample period. Although its curve moved leftward after 2020 and became more concentrated by 2023, its overall distribution still remained to the right of the low- and medium-level regions, indicating that its relatively high-intensity characteristic had not been fully eliminated. At the national level, the kernel density curves reflected the combined evolution of the three regional types: the overall distribution moved leftward and became more concentrated after 2020, yet a residual right tail remained, suggesting that nationwide decline coexisted with persistent high-intensity observations in a few provinces (Fig. 2).

Regional Disparities and Source Decomposition of Pesticide Use Intensity in Grain Crops

The GE0 results show that the overall interprovincial disparity in pesticide use intensity first narrowed slightly, then expanded, and finally fluctuated at a relatively high level. The GE0 index declined from 0.216 in 2005 to 0.196 in 2007, rose to 0.283 in 2013, and then fluctuated within the range of 0.238~0.262, ending at 0.248 in 2023. This indicates that although

Table 1. Regional disparities in pesticide use intensity in grain crops.

Year	Theil index	Inter-regional disparity	Intra-regional disparity	Low-NQP region	Medium-NQP region	High-NQP region
2005	0.216	0.029	0.186	0.339	0.145	0.076
2006	0.207	0.030	0.177	0.329	0.118	0.083
2007	0.196	0.024	0.172	0.311	0.118	0.087
2008	0.218	0.022	0.196	0.370	0.123	0.095
2009	0.255	0.022	0.233	0.496	0.109	0.095
2010	0.272	0.021	0.251	0.521	0.129	0.104
2011	0.279	0.027	0.251	0.545	0.095	0.114
2012	0.265	0.027	0.238	0.484	0.104	0.127
2013	0.283	0.031	0.253	0.525	0.098	0.136
2014	0.268	0.027	0.241	0.481	0.105	0.136
2015	0.270	0.028	0.242	0.476	0.101	0.148
2016	0.262	0.025	0.237	0.445	0.114	0.151
2017	0.261	0.025	0.236	0.456	0.101	0.151
2018	0.238	0.022	0.215	0.398	0.104	0.143
2019	0.250	0.024	0.226	0.432	0.108	0.138
2020	0.247	0.025	0.222	0.424	0.104	0.138
2021	0.251	0.028	0.224	0.425	0.113	0.133
2022	0.247	0.028	0.219	0.412	0.114	0.132
2023	0.248	0.028	0.220	0.426	0.108	0.125

the disparity level decreased from its peak, it did not return to the initial level observed at the beginning of the study period.

Decomposition results further show that intra-regional disparity was consistently the dominant source of overall disparity. In 2005, intra-regional disparity accounted for about 86.1% of the total, and by 2023 its share had risen to about 88.7%. Over the full sample period, inter-regional disparity remained relatively stable, whereas intra-regional disparity closely tracked the movement of the overall GE0 index. This suggests that differences in pesticide use intensity were shaped more by variation among provinces within the same NQP group than by average differences across the three regional types.

Among the three regional types, the low-level region exhibited the largest and most persistent internal disparity. Its within-region GE0 rose from 0.339 in 2005 to 0.545 in 2011 and remained as high as 0.426 in 2023. The medium-level region displayed the lowest internal disparity throughout the period, fluctuating only slightly within a relatively narrow range and ending at 0.108 in 2023. The high-level region showed a mid-period increase followed by a late-period decline, rising from 0.076 in 2005 to 0.151 in 2016-2017 before falling to 0.125 in 2023. Overall, these results indicate that the low-level region was the principal contributor to intra-regional divergence, while the medium-level region remained comparatively stable and the high-level region showed signs of convergence in the later stage (Table 1).

State Transition Characteristics of Pesticide Use Intensity in Grain Crops

Table 2 shows that the Markov transition matrix of pesticide use intensity in grain crops exhibited clear diagonal dominance during 2005-2023, indicating strong state persistence across all three states. No direct transitions were observed between the low-intensity and high-intensity states; instead, transitions occurred mainly between adjacent states, namely between low and medium intensity and between medium and high intensity. This pattern suggests that changes in pesticide use intensity were characterized primarily by gradual adjustment rather than abrupt cross-level shifts.

A stage-wise comparison further indicates that state mobility was relatively stronger during 2005-2010, especially for the medium-intensity state. During 2011-2016, the low-intensity state became more stable, while limited bidirectional transitions between the medium- and high-intensity states remained. During 2017-2023, the persistence probabilities of all three states increased further, and adjacent-state transition probabilities generally declined, indicating that the interprovincial state structure became more stable in the later period.

Taken together, these results suggest that although pesticide use intensity declined at the aggregate level, the relative positions of provinces did not change rapidly. Instead, the evolution process was characterized by the coexistence of overall improvement and strengthened state lock-in, which is consistent with the evidence of declining average intensity but persistent disparity.

Driver Decomposition Results of Changes in Pesticide Use Intensity in Grain Crops

Table 3 shows that the stage-wise changes in pesticide use intensity differed across regions, but an

Table 2. Transition probability matrix.

Stage	t/t+1	Low-intensity state	Medium-intensity state	Medium-intensity state
2005-2010	Low-intensity state	0.9412 (48)	0.0588 (3)	0.0000 (0)
	Medium-intensity state	0.0800 (4)	0.8600 (43)	0.0600 (3)
	High-intensity state	0.0000 (0)	0.0556 (3)	0.9444 (51)
2011-2016	Low-intensity state	0.9804 (50)	0.0196 (1)	0.0000 (0)
	Medium-intensity state	0.0000 (0)	0.9216 (47)	0.0784 (4)
	High-intensity state	0.0000 (0)	0.0755 (4)	0.9245 (49)
2017-2023	Low-intensity state	0.9839 (61)	0.0161 (1)	0.0000 (0)
	Medium-intensity state	0.0000 (0)	0.9508 (58)	0.0492 (3)
	High-intensity state	0.0000 (0)	0.0476 (3)	0.9524 (60)
2005-2023	Low-intensity state	0.9730 (180)	0.0270 (5)	0.0000 (0)
	Medium-intensity state	0.0276 (5)	0.9061 (164)	0.0663 (12)
	High-intensity state	0.0000 (0)	0.0677 (13)	0.9323 (179)

Table 3. Driving factors of pesticide use intensity in grain crops.

Regions	Stage	ΔI	Total pesticide use effect	Grain-crop cultivated land area effect	Total cultivated land area effect	Grain output effect
Low-NQP region	2005-2010	0.4734	0.7146	0.1948	-0.0916	-0.3444
Low-NQP region	2011-2015	-0.1640	0.1379	0.0613	-0.0903	-0.2727
Low-NQP region	2016-2020	-0.5918	-0.4758	-0.0330	-0.0146	-0.0684
Low-NQP region	2021-2023	-0.1008	-0.0549	0.0293	-0.0257	-0.0495
Medium- NQP region	2005-2010	0.2904	0.5904	0.1988	-0.1353	-0.3634
Medium- NQP region	2011-2015	-0.1594	0.0967	0.1071	-0.0945	-0.2686
Medium- NQP region	2016-2020	-0.4374	-0.4414	-0.0159	-0.0063	0.0261
Medium- NQP region	2021-2023	-0.0800	-0.0611	0.0100	-0.0168	-0.0121
High- NQP region	2005-2010	0.0876	0.2020	0.0489	0.0685	-0.2318
High- NQP region	2011-2015	-0.2331	-0.1192	0.1146	-0.0556	-0.1728
High- NQP region	2016-2020	-0.5544	-0.4605	-0.0609	0.0087	-0.0418
High- NQP region	2021-2023	-0.1431	-0.1161	0.0061	-0.0188	-0.0142
China	2005-2010	0.1919	0.4016	0.1502	-0.0459	-0.3139
China	2011-2015	-0.2150	-0.0031	0.1051	-0.0806	-0.2363
China	2016-2020	-0.5149	-0.4558	-0.0371	-0.0024	-0.0196
China	2021-2023	-0.1155	-0.0867	0.0137	-0.0207	-0.0218

overall common pattern can still be identified. Pesticide use intensity generally increased during 2005-2010, entered an overall downward trajectory after 2011, declined most sharply during 2016-2020, and then continued to decrease at a slower pace during 2021-2023. Among all regional types and the national aggregate, the most pronounced decline occurred during 2016-2020, indicating that this period was the key adjustment stage.

From the perspective of decomposition structure, the total pesticide use effect and the grain output effect were the two most important drivers of change, although their roles varied across stages. In the early period, the total pesticide use effect and the grain-crop cultivated area effect generally exerted upward pressure on intensity, whereas the grain output effect contributed to a decline. As a result, some regions still recorded net increases in intensity during 2005-2010. In the middle and later periods, especially during 2016-2020, the total pesticide use effect shifted from positive to strongly negative and became the main force driving the decline in pesticide use intensity. The grain output effect continued to contribute to the decline in most cases, although its relative contribution weakened compared with earlier stages.

Regional heterogeneity was also evident. In the low- and medium-level regions, the early increase in intensity was mainly associated with the positive effects of total pesticide use and grain-crop cultivated area, whereas the later decline was driven chiefly by the negative shift in the total pesticide use effect and the continued contribution of grain output. In the high-level region, the net increase in the early stage was comparatively smaller, and the transition to decline occurred earlier and more sharply after 2011, particularly during 2016-2020. At the national level, the decomposition pattern was broadly similar to the regional results, indicating that the decline in pesticide use intensity was jointly shaped by reductions in total pesticide input, adjustments in cultivated land-related factors, and the output-dilution effect associated with grain production.

Discussion

This study shows that pesticide use intensity in China's grain crops declined overall during 2005-2023, but the decline was neither uniform nor linear across regions. High-NQP regions maintained the highest intensity levels over the long run, yet they also recorded the largest absolute reductions. This pattern suggests that regions with stronger technological capacity and more advanced production systems may initially operate at relatively high input intensity because of more intensive cultivation, more complex pest pressure, and stronger output orientation, but they may also possess greater capacity to reduce pesticide dependence once regulation, service systems, and technology upgrading begin to take effect. In this sense, the larger decline observed in high-NQP regions should not be interpreted simply as a stronger "starting advantage", but rather as evidence that technologically and organizationally more advanced regions are better positioned to convert policy pressure into measurable input adjustment. This interpretation is broadly compatible with the finding that pesticide management policies in China can significantly reduce pesticide use intensity [18], while the actual reduction effect depends on regulatory transmission and local implementation conditions [19].

From the perspective of distributional evolution, the leftward shift, higher peak, and narrowing spread of the kernel density curves indicate that pesticide use intensity generally moved downward and became more concentrated. However, the persistence of the right tail is equally important. It implies that average improvement did not eliminate high-intensity provinces, and that national convergence remained incomplete. This residual right tail is likely associated with the combined effects of stronger pest pressure, more input-intensive planting structures, multiple-cropping systems, and slower substitution of ecological pest-control technologies in some provinces. Therefore, the right tail should be understood not as a statistical remainder, but as a substantive sign that some production systems still rely structurally on higher pesticide input per unit of grain output. This also helps explain why the decline in national average intensity did not automatically lead to a synchronized disappearance of high-intensity observations. Such a result is consistent with broader studies on agricultural green and low-carbon transformation, which show that average improvement may coexist with persistent high-value clusters or tail-end risks [20]. It also accords with county-scale evidence that fertilizer and pesticide use may vary substantially even within the same macro-region.

A more important finding of this study is that intra-regional disparity, rather than inter-regional disparity, remained the dominant source of total inequality throughout the sample period. This result differs in emphasis from studies that mainly interpret regional differentiation through broad east–central–west divisions or aggregate development gradients [21, 22]. The present finding suggests that once provinces are grouped by NQP level, the most consequential variation no longer lies primarily between the three broad groups, but within them. In substantive terms, this means that provinces with similar long-run development-stage characteristics may still diverge substantially in pesticide use intensity because of differences in governance effectiveness, agricultural extension coverage, socialized plant-protection services, crop structure, production organization, and farmers' risk-management behavior. Existing studies have shown that environmental regulation affects pesticide use in China, but the strength and direction of that effect are conditioned by local institutional and production contexts [23]. Likewise, research on farmer pesticide-use behavior has emphasized that risk perception and risk attitude shape chemical-input decisions in ways that can reinforce local divergence even under shared macro-policy settings [24]. Therefore, the dominance of intra-group disparity found here does not contradict the importance of macro-regional gradients; rather, it indicates that policy effectiveness is filtered through local implementation capacity and farm-level behavioral responses.

The Markov-chain results further show strong diagonal dominance and a clear absence of direct transitions between the low- and high-intensity states. This means that pesticide-use adjustment in grain production is better described as an evolutionary process than as a discontinuous transformation. Such path dependence can be explained by several mechanisms. First, pesticide-use routines are embedded in repeated seasonal decision-making, and once farmers, local service providers, and production organizations form stable pest-control practices, these practices tend to persist. Second, agricultural input adjustment is constrained by risk aversion: under uncertain pest outbreaks, producers often prefer incremental reduction rather than abrupt cuts in chemical use [25]. Third, local service systems, crop structures, and agronomic calendars generate inertia that makes adjacent-state transition much more likely than leapfrogging from high to low intensity in a short period. At the same time, path dependence should not be understood as immutability. Policy reforms, extreme climate anomalies, and sudden pest outbreaks may disturb existing transition trajectories, but in most cases they are more likely to reshape the speed and direction of gradual adjustment than to produce immediate cross-level jumps. This is why the coexistence of overall decline and stronger state lock-in is not contradictory: average intensity can continue to fall even while the relative ranking structure across provinces remains fairly stable. This interpretation is broadly consistent with studies arguing that agricultural green development tends to evolve through gradual adjustment and spatial lock-in rather than abrupt restructuring [26, 27].

The LMDI decomposition results provide a mechanism-based explanation for the above evolution. In the early stage, total pesticide use and grain-crop cultivated area tended to exert upward pressure on pesticide use intensity, whereas grain output played a countervailing role. This suggests that when scale expansion and input demand dominated, the dilution effect of output growth was not sufficient to offset the increase in chemical dependence in some regions. In the middle and later stages, especially during 2016-2020, the total pesticide use effect turned strongly negative

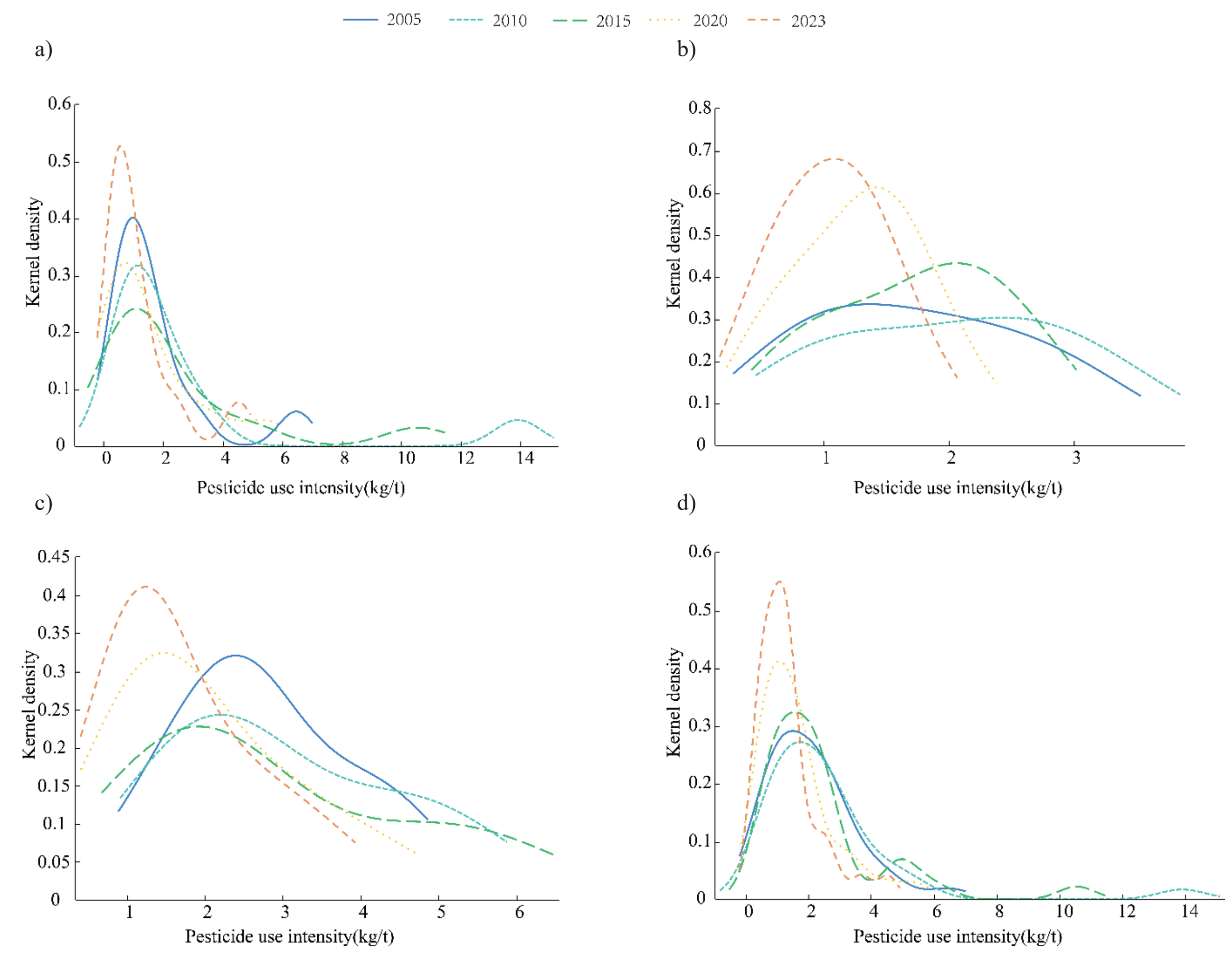

Fig. 2. Kernel density estimation results of pesticide use intensity in grain crops.

and became the main driver of decline, while the grain output effect continued to contribute to lower intensity in most cases. This shift indicates that the main force underlying the reduction in pesticide use intensity gradually moved from output-side dilution to a more direct reduction in chemical input itself. In other words, the decline in intensity was increasingly shaped by changes in pesticide-use behavior rather than by output growth alone. This interpretation is consistent with decomposition studies in agricultural environmental governance showing that once regulatory constraints strengthen and greener technologies diffuse, the intensity effect can progressively outweigh the scale effect [28]. At the same time, this mechanism also supports the view that input reduction does not necessarily imply damage to food security, but depends on the maturity of substitution technologies and the adaptability of local production systems [29].

Taken together, these findings have three implications for differentiated pesticide-reduction policy. First, policy attention should move beyond aggregate reduction targets and place greater emphasis on identifying structurally persistent high-intensity provinces in the right tail. Second, because intra-group heterogeneity dominates, policy design should not rely solely on broad regional labels; instead, more effort should be directed toward improving local agricultural extension, pest forecasting, socialized spraying services, and ecological substitution technologies within each development group. Third, given the strong path dependence revealed by the Markov analysis, pesticide reduction should be understood as a medium- to long-term institutional and technological transition rather than a short-run administrative adjustment. In this regard, integrated pest management and precision application technologies remain important because they reduce dependence on chemical control while helping maintain production resilience [30].

Several limitations still need to be acknowledged. First, pesticide use in grain crops was estimated through an area-proportional allocation method, which is suitable for interprovincial comparison but cannot fully reflect crop-specific application differences. Second, the NQP level in this study was used as a stratification framework rather than as a formally tested explanatory mechanism, so the causal channels through which development-stage characteristics affect pesticide use intensity still require further verification. Third, the indicator used here is quantity-based and does not distinguish pesticide type, toxicity, or exposure risk. Recent evidence suggests that declines in applied pesticide quantity and changes in toxicity trends may diverge, meaning that a reduction in kg/t does not necessarily imply a proportional reduction in ecological risk [30]. Finally, although province-level panel data are well suited to identifying long-run national patterns, they may mask substantial intra-provincial heterogeneity. Future research could therefore combine sub-provincial panel data, crop-specific pesticide information, and toxicity-weighted indicators to further test whether the patterns identified here remain robust at finer spatial scales.

Conclusions

Based on panel data for 31 provincial-level regions in China from 2005 to 2023, this study systematically examined the spatiotemporal evolution, regional disparities, state transitions, and driving factors of pesticide use intensity in grain crops. The results show that pesticide use intensity generally declined over the study period, but with clear stage-specific characteristics and regional heterogeneity. High-level regions consistently maintained relatively high pesticide use intensity while also exhibiting the largest reductions, whereas medium- and low-level regions declined simultaneously and became more concentrated in the later period. Kernel density estimation (Fig. 2) indicates an overall leftward shift in the national and regional distributions, suggesting a certain degree of convergence; however, the persistent right tail shows that a small number of provinces remained at relatively high intensity levels. GE0 decomposition further reveals that overall disparities were driven mainly by intra-regional heterogeneity rather than by differences in average levels across regions. Markov chain analysis shows strong path dependence, with state transitions occurring primarily between adjacent levels. LMDI decomposition indicates that the total pesticide use effect and the grain output effect were the key drivers of changes in pesticide use intensity, and that the negative shift in the total pesticide use effect played a particularly important role in accelerating the decline during 2016-2020.

Overall, pesticide reduction in China's grain sector did not follow a simple and uniform convergence path, but instead exhibited a pattern in which overall improvement, within-group differentiation, and gradual adjustment coexisted. Therefore, future policies should, while safeguarding food security, place greater emphasis on identifying persistent high-intensity provinces, strengthening targeted governance within regions, and improving green pest-control technologies and socialized service systems, so as to promote a more stable, efficient, and environmentally sustainable transformation of grain production.

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AI Usage Disclosure Statement

During the preparation of this manuscript, the authors used OpenAI's ChatGPT (GPT-5.4) solely for English translation and language polishing because the authors are not native English speakers. The AI tool was not used for research design, data collection, data generation, data processing, statistical analysis, result interpretation, reference generation, or figure preparation. All AI-assisted translations and language revisions were carefully reviewed, verified, and corrected by the authors to ensure linguistic accuracy and consistency with the original scientific meaning. The authors take full responsibility for the accuracy, integrity, and content of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

References

1. WU Y., XI X., TANG X., LUO D., GU B., LAM S. K., VITOUSEK P. M., CHEN D. Policy distortions, farm size, and the overuse of agricultural chemicals in China. Proceedings of the National Academy of Sciences USA, **115** (27), 7010, **2018**.
2. ERDIWANSYAH, NURMAN S., MASYUDI, SAUDAH, IRHAMNI, DIANA, HIDAYAT F. Global Trends in Agricultural Waste-Based Bioplastic Research: A Scientometric Review. Journal of Human, Earth, and Future, **6** (1), 234, **2025**.
3. TANG F.H.M., LENZEN M., MCBRATNEY A., MAGGI F. Risk of pesticide pollution at the global scale. Nature Geoscience, **14** (4), 206, **2021**.
4. SHUQIN J.I.N., FANG Z. Zero Growth of Chemical Fertilizer and Pesticide Use:China's Objectives, Progress and Challenges. Journal of Resources and Ecology, **9** (1), 50, **2018**.
5. WU K., CHEN C. Spatiotemporal Differentiation of Fertilizer and Pesticide Use and Its Driving Factors in the Yangtze River Delta of China: An Analysis at the County Scale. Land, **14** (6), 1180, **2025**.
6. MöHRING N., BA M.N., BRAGA A.R.C., GABA S., GAGIC V., KUDSK P., LARSEN A., MESNAGE R., NIGGLI U., QAIM M., SCHREINEMACHERS P., STAMM C., DE VRIES W., FINGER R. Expected effects of a global transformation of agricultural pest management. Nature Communications, **16** (1), 10901, **2025**.
7. KARAKULOV F., MENGLIKULOV B., MAMASADIKOV A., KHOLBUTAEVA S., MUKHTOROV A., ABDULKHAEVA G., GAFUROVA D., RUZIYEV S., ABLATDINOV S., DURMANOV A. The Impact of Climate-Smart Technology Adoption on Agricultural Productivity and Environmental Sustainability. Emerging Science Journal, **9** (6), 3087, **2025**.
8. WIJITKOSUM S., SRIBURI T., TOONSIRI P. Effect of One-Time Application of Biochar and Compost on Soil and Maize During 5-Time Consecutive Periods of Crop Cultivation. Emerging Science Journal, **9** (1), 114, **2025**.
9. CHAI C., LI Y., WEN R., ZHANG H., ZHANG B., XING P., SUN Y., ZHU H., HOU G., WANG H., NIU W., ZHENG W., KONG X. Detecting farmland green production efficiency considering Sustainable Development Goals (SDGs) in the Yellow River Basin: Dynamics, drivers, and challenges. Geography and Sustainability, **7** (2), 100418, **2026**.
10. ZHANG Z., JIN G. Spatiotemporal differentiation of carbon budget and balance zoning: Insights from the middle reaches of the Yangtze River Urban Agglomeration, China. Applied Geography, **167**, 103293, **2024**.
11. HUANG Q., GUO W., WANG Y. A Study of the Impact of New Quality Productive Forces on Agricultural Modernization: Empirical Evidence from China. Agriculture, **14** (11), 1935, **2024**.
12. LEI X., ZHAO W., DU H. Study on the impact of new quality productive forces on agricultural green production efficiency. Scientific Reports, **15** (1), 20652, **2025**.
13. YANG M., CHU J., LI Z., LIU X., YU F., SUN F. An Examination of Regional Variations in Pesticide Usage and Grain Yield in China Before and After the Double Reduction Policy's Adoption. Polish Journal of Environmental Studies, **32** (2), 1887, **2023**.
14. ZHU X., SHAO X. Spatiotemporal evolution of agricultural carbon emissions intensity in China and analysis of influencing factors. Scientific Reports, **15** (1), 19202, **2025**.
15. WANG R., FENG Y. Research on China's agricultural carbon emission efficiency evaluation and regional differentiation based on DEA and Theil models. International Journal of Environmental Science and Technology. **18** (6), 1453, **2021**.
16. RAJU A. Applications of Markov chains in climate change modelling: A comprehensive review of advances, challenges, and future directions. Ecological Modelling, **514**, 111470, **2026**.
17. WANG M., HUANG X., DONG Y., SONG Y., WANG D., LI L., QI X., LIN N. Spatiotemporal drivers of agricultural non-point source pollution: A case study of the Huang-Huai-Hai Plain, China. Journal of Environmental Management, **370**, 122606, **2024**.
18. CHEN J., HE P. Using the synthetic control method to evaluate pesticide reduction effect: A study based on China's pesticide management policy. Journal of Environmental Management, **394**, 127358, **2025**.
19. JI Y., LIU H., SHI Y. Will China's fertilizer use continue to decline? Evidence from LMDI analysis based on crops, regions and fertilizer types. PLoS One, **15** (8), e0237234, **2020**.
20. HE Z., FU P., MENG Y. Analysis of spatial disequilibrium and convergence in China's agricultural green and low-carbon transformation. Carbon Balance and Management, **20** (1), 62, **2025**.
21. HOU J., LI X., TANG Y., HOU B., CHEN F. The Impact of Environmental Regulation on Pesticide Use in China. Agriculture, **15** (8), 825, **2025**.
22. LI X., GUAN R. How Does Agricultural Mechanization Service Affect Agricultural Green Transformation in China? International Journal of Environmental Research and Public Health, **20** (2), 1655, **2023**.
23. ZHOU F., WEN C. Research on the Level of Agricultural Green Development, Regional Disparities, and Dynamic Distribution Evolution in China from the Perspective of Sustainable Development. Agriculture, **13** (7), 1441, **2023**.

24. YU J., SUN Y., WEI F. Green Development of Chinese Agriculture from the Perspective of Bidirectional Correlation. Agriculture, **14** (9), 1628, **2024**.
25. HE Y., FANG G., QI C., GU Y. Research on the Spatial Correlation Network and Driving Mechanism of Agricultural Green Development in China. Agriculture, **15** (7), 693, **2025**.
26. PAN D., HE M., KONG F. Risk attitude, risk perception, and farmers' pesticide application behavior in China: A moderation and mediation model. Journal of Cleaner Production, **276**, 124241, **2020**.
27. MEYS E.L., WILLDEN S.A., INGWELL L.L., KOHLI G., ATHEY K.J. A review of integrated pest management practices in high tunnel specialty crop production. Crop Protection, **202**, 107530, **2026**.
28. HU J., CHI L., XING L., MENG H., ZHU M., ZHANG J., WU J. Decomposing the decoupling relationship between energy consumption and economic growth in China's agricultural sector. Science of The Total Environment, **873**, 162323, **2023**.
29. HU Y., LIU Y. Impact of fertilizer and pesticide reductions on land use in China based on crop-land integrated model. Land Use Policy, **141**, 107155, **2024**.
30. WOLFRAM J., BUSSEN D., BUB S., PETSCHICK L.L., HERRMANN L.Z., SCHULZ R. Increasing applied pesticide toxicity trends counteract the global reduction target to safeguard biodiversity. Science, **391** (6785), 616, **2026**.