

Article

Research on the Impact of Non-Agricultural Employment on Agricultural Carbon Emission Reduction: An Empirical Analysis Based on 295 Prefecture-Level Cities in China

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Abstract

In the context of China's Carbon Peaking and Carbon Neutrality Goals, understanding how non-agricultural employment affects agricultural carbon emission intensity is critical for achieving green and sustainable agricultural development. This study asks whether the reallocation of labor away from agriculture increases or reduces agricultural carbon emission intensity, through which transformation-related pathways this relationship may operate, and whether the relationship changes across development stages and spatially connected regions. Using panel data from 295 prefecture-level cities in China from 2011 to 2023, this study constructs a factor-substitution framework and applies fixed-effects models, potential pathway analysis, threshold models, and Spatial Durbin Models. The results show that non-agricultural employment has a significant inverted U-shaped association with agricultural carbon emission intensity: at relatively low levels it is associated with higher emission intensity, whereas beyond the estimated turning point it is associated with lower emission intensity. Non-agricultural employment is also systematically associated with agricultural structural adjustment, mechanization transformation, and AI-related patenting activity, which are interpreted as potential pathways rather than definitive causal mediation channels. Threshold results indicate that economic development and urbanization condition the marginal effect of non-agricultural employment, while spatial estimates show that the nonlinear relationship extends to neighboring regions through significant spillover effects. These findings suggest that agricultural carbon-reduction policies should distinguish between cities at different stages of labor reallocation, promote low-carbon forms of capital and technology substitution, and strengthen cross-regional coordination in agricultural producer services and green technology diffusion.

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1. Introduction

Under the constraints of global climate change and the “carbon peaking–carbon neutrality” targets, the agricultural sector—characterized by its dual role as both a source of carbon emissions and a carbon sink—has become a pivotal domain for achieving a green and low-carbon transition [1,2]. In China, agricultural carbon emissions are shaped by food-security requirements, production practices, factor inputs, and technological pro-

gress [3,4]. At the same time, the agricultural sector is undergoing profound factor reallocation. Rural labor has continued to shift from agriculture to non-agricultural sectors, while mechanization, water-saving irrigation, digital technologies, and agricultural producer services have developed rapidly [5,6]. These changes raise a central research question: how is non-agricultural employment associated with agricultural carbon emission intensity, and under what conditions does this relationship become emission-increasing or emission-reducing?

This question is important because non-agricultural employment may have theoretically ambiguous effects on agricultural carbon emission intensity. On the one hand, labor outflow changes the relative scarcity of production factors and may induce farmers to substitute labor with machinery, fertilizers, pesticides, diesel, and other capital- or energy-intensive inputs, thereby increasing carbon emission intensity in the short run [7–9]. On the other hand, when labor reallocation is accompanied by land transfer, scale operation, agricultural service outsourcing, digital management, and green technological upgrading, it may improve resource allocation and reduce carbon emission intensity in the long run [10–14]. Therefore, the key issue is not whether non-agricultural employment simply increases or decreases agricultural carbon emission intensity, but whether its effect follows a nonlinear path driven by factor substitution and agricultural transformation.

Existing research provides several relevant but not fully consistent insights. Studies on rural labor transfer and agricultural modernization generally find that labor outflow can improve factor allocation, promote land transfer, and raise technical efficiency [15–23]. However, structural transformation may also generate environmental externalities when producers rely on low-cost or high-carbon practices to compensate for labor shortages [24]. Related evidence shows that off-farm employment patterns differ across gender groups [25], while capital-for-labor substitution may increase chemical fertilizer use in agriculture [26,27]. Meanwhile, agriculture functions both as a carbon source and a carbon sink and therefore plays an important role in achieving China's carbon peaking and carbon neutrality goals [28–32]. Recent studies also discuss crop-production optimization and greenhouse-gas reduction strategies in China's agricultural sector [33,34]. Migration-related evidence suggests that labor mobility may affect agricultural engagement and production adjustment [35], while rural labor migration, non-agricultural employment, and related production-service mechanisms have been linked to agricultural carbon emissions, fertilizer use, and carbon-emission efficiency in China [36–41].

The literature also indicates that agricultural carbon emissions are spatially clustered and regionally heterogeneous [42–48]. This means that the same change in employment structure may produce different carbon outcomes across regions depending on land endowment, grain-production responsibility, service-market development, and access to green technologies. In addition, digital agriculture and smart equipment can improve input allocation and reduce carbon footprints in some settings [49–52], but patenting activity or digital infrastructure does not necessarily imply actual adoption in agricultural production.

These findings suggest a need to connect labor reallocation, factor substitution, development-stage conditions, and spatial linkages in one coherent empirical framework. A purely linear model may miss the possibility that non-agricultural employment first raises and later reduces carbon emission intensity. Likewise, analyses that ignore neighboring regions may understate spillovers transmitted through labor mobility, technology diffusion, machinery-service markets, and regional agricultural supply chains.

Although the existing literature provides an important foundation, three limitations remain. First, many studies focus on household, county, or provincial data; emphasize single emission sources such as fertilizer use; or examine agricultural carbon emissions without directly modeling non-agricultural employment within a unified nonlinear and spatial framework. Second, evidence based on prefecture-level cities remains relatively

limited, even though this scale is well-suited to capturing differences in local labor markets, agricultural production conditions, urbanization, and policy implementation. Third, the pathways and spatial implications of non-agricultural employment are often discussed separately, making it difficult to assess whether local effects and spillover effects are consistent with the same theoretical mechanism.

To address these gaps, this study uses panel data for 295 prefecture-level cities in China from 2011 to 2023 to examine the nonlinear relationship between non-agricultural employment and agricultural carbon emission intensity. The analysis focuses on three connected questions: whether the relationship follows an inverted U-shaped pattern; whether non-agricultural employment is associated with transformation-related pathways such as mechanization, agricultural structure, and digital innovation potential; and whether the relationship varies across development thresholds and spatially connected regions.

Compared with provincial-level studies, prefecture-level data do not simply provide more observations; they allow the analysis to distinguish local labor-market conditions, production structures, land endowments, and urban-agglomeration contexts that would be averaged out at higher administrative scales. Compared with county-level data, prefecture-level cities are also meaningful policy units for coordinating agricultural services, land transfer, technological extension, and cross-county environmental governance. This scale therefore helps link empirical estimates more directly to regional policy design.

This study contributes to the literature in three ways. First, it clarifies the theoretical ambiguity in the relationship between non-agricultural employment and agricultural carbon emission intensity. By emphasizing factor substitution, the study explains why labor reallocation may initially increase carbon intensity through energy- and input-intensive substitution, but later reduce carbon intensity through scale operation, service outsourcing, and green technological upgrading. Second, from a data and empirical-design perspective, this study provides prefecture-level evidence that links labor reallocation, agricultural production conditions, and spatial policy contexts more directly than provincial-level analyses. The prefecture-level scale helps reveal within-province heterogeneity in labor mobility, land endowment, grain-production functions, urban-agglomeration status, and agricultural service-market development. The empirical models are not used merely to expand the econometric toolkit; rather, they are organized around one integrated question: whether the carbon effect of non-agricultural employment is nonlinear, conditioned by development thresholds, and transmitted across neighboring regions through spatial linkages. Third, it explicitly incorporates threshold conditions and spatial spillover channels. The study not only examines whether economic development and urbanization change the marginal effect of non-agricultural employment, but also tests whether local labor reallocation is associated with agricultural carbon emission intensity in neighboring regions through agricultural service markets, technology diffusion, and regional production linkages.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and research hypotheses. Section 3 introduces the data, variables, and empirical models. Section 4 presents the empirical results, including baseline regressions, potential pathway analysis, threshold effects, robustness tests, heterogeneity analysis, and spatial spillover effects. Section 5 discusses the findings in relation to the existing literature. Section 6 concludes and proposes policy implications.

The theoretical mechanism underlying this framework is further developed in Section 2 and summarized in Figure 1, which illustrates how non-agricultural employment affects agricultural carbon emission intensity through factor substitution, transformation-related pathways, threshold conditions, and spatial spillovers.

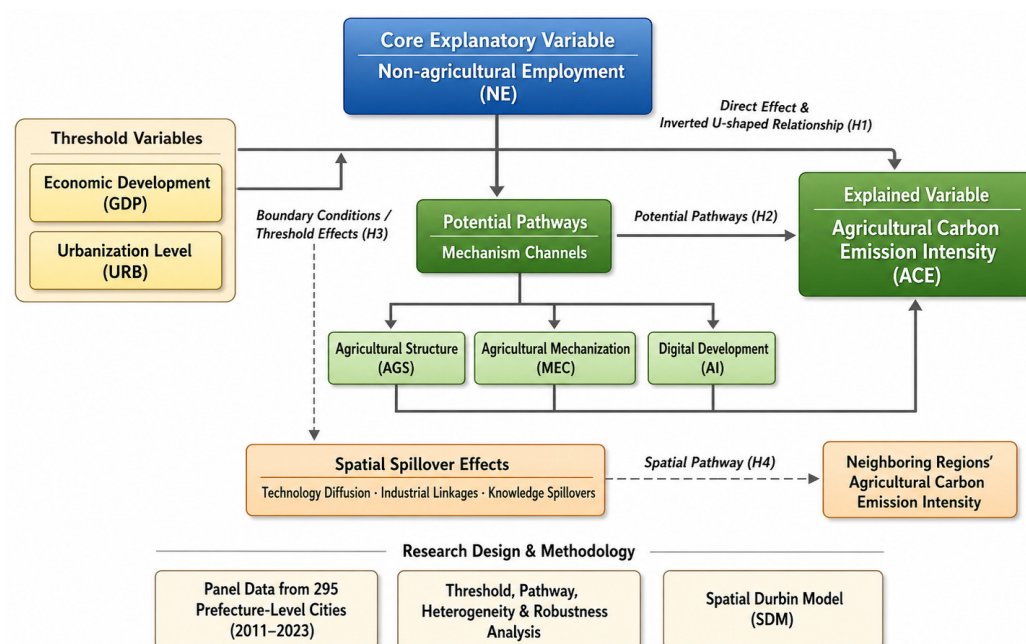


Figure 1. Theoretical Framework of the Research Mechanism. Source: drafted by the authors using Microsoft PowerPoint.

2. Literature Review and Research Hypotheses

Driven by the process of urbanization, the non-agricultural transfer of rural labor in China has become a key force reshaping agricultural production patterns [53]. Non-agricultural employment not only alters the structure of agricultural factor endowments but also affects agricultural carbon emission pathways through the reallocation of capital, technology, and organizational forms [54,55].

2.1. Overall Mechanism Linking Non-Agricultural Employment and Agricultural Carbon Emission Intensity

In this study, factor substitution is treated as the dominant mechanism linking non-agricultural employment and agricultural carbon emission intensity. Non-agricultural employment changes the relative scarcity and cost of agricultural labor, which induces adjustments in the combination of labor, capital, technology, and organizational forms. Mechanization, agricultural structural adjustment, digital development, and spatial spillovers are therefore not treated as independent and unrelated channels, but as different manifestations of factor substitution across production stages and regional contexts. This perspective helps organize the potentially emission-increasing and emission-reducing effects of labor reallocation within a unified analytical framework.

Under the traditional dual economic structure, the agricultural sector is characterized by surplus labor, while the expansion of non-agricultural sectors provides absorption capacity. According to the Lewis dual-sector model, the transfer of labor to non-agricultural sectors releases productive factors from agriculture, facilitating a gradual shift toward capital- and technology-intensive production [56]. In essence, non-agricultural employment represents a process of factor reallocation and institutional adjustment: it releases low-efficiency labor while promoting the restructuring of production organization and management models, thereby laying the foundation for a green and low-carbon agricultural transition. As labor becomes increasingly scarce, equilibrium wages rise, increasing the relative cost of labor and inducing substitution toward capital and technology. Within

the framework of factor substitution theory, this scarcity and rising cost of labor induce the substitution of labor by capital and technology [57].

Non-agricultural employment may induce agricultural producers to adopt mechanization, drones, intelligent monitoring technologies, and other labor-saving inputs [58–60]. However, such substitution does not necessarily reduce carbon emission intensity immediately. In the early stage of labor outflow, producers may rely on conventional machinery, diesel, fertilizers, pesticides, and other energy- or input-intensive substitutes to maintain agricultural output, which can increase carbon emission intensity. As labor reallocation deepens and is accompanied by land transfer, scale operation, agricultural producer services, and green technological upgrading, factor substitution may gradually shift from simple labor-saving substitution to efficiency-oriented and energy-saving substitution. Under these conditions, improved input allocation and production efficiency may reduce carbon emission intensity per unit of output [61].

However, the effects vary across regions and development stages. In areas experiencing rapid labor outflows but lacking sufficient technological and capital support, farmers may rely on high-carbon inputs such as fertilizers and pesticides to compensate for labor shortages, thereby increasing emissions in the short term. This suggests that the impact of non-agricultural employment on agricultural carbon emissions is both stage-specific and structurally heterogeneous: it generates emission-reduction effects in regions with adequate technological and organizational conditions, but may induce carbon rebound where factor substitution is constrained. Based on this, the following hypothesis is proposed:

H1: *Non-agricultural employment has a nonlinear impact on agricultural carbon emission intensity. Specifically, agricultural carbon emission intensity initially increases with non-agricultural employment but decreases after non-agricultural employment reaches a higher level.*

2.2. Indirect Mechanisms from the Perspectives of Structural Optimization and Factor Allocation

Under the dominant factor-substitution mechanism, non-agricultural employment may be associated with several transformation-related pathways. These pathways do not represent independent mechanisms detached from factor substitution. Rather, they reflect how labor scarcity and rising relative labor costs induce producers to adjust machinery use, production structure, digital innovation capacity, and organizational forms. Therefore, this section focuses on three observable pathways closely related to agricultural transformation: mechanization, agricultural structural adjustment, and digital development.

The first pathway concerns technological adjustment. Labor outflow reduces the availability of agricultural labor and increases labor costs, creating incentives for producers to adjust input combinations and adopt labor-saving technologies [62,63]. Agricultural mechanization and digital technologies may improve production efficiency, facilitate scale management, and support precision agricultural practices. However, these changes should not be interpreted as uniformly emission-reducing, because machinery use and digital equipment may also involve energy consumption and embodied carbon. Consequently, labor transfer may be associated with changes in technological conditions that are relevant to agricultural carbon emission intensity, but the direction of the effect may depend on the stage and form of technological substitution.

The second pathway concerns agricultural structural adjustment. Labor outflow may encourage producers to adjust production structures and reallocate resources from labor-intensive activities toward capital- and technology-intensive activities. In some regions, this adjustment may support facility agriculture, fruit and vegetable cultivation, large-scale livestock production, or other forms of specialized production [64–66]. In addition, land consolidation toward large-scale operators—such as family farms, cooperatives, and

agribusiness firms—may strengthen capital accumulation and technological absorption capacity [67], facilitating the adoption of green practices including straw return, crop–livestock integration, and clean energy substitution [68]. Nevertheless, structural adjustment may also increase emissions if it relies on energy-intensive inputs or high-carbon production modes.

Overall, non-agricultural employment may be associated with changes in agricultural production organization, resource allocation, and technological development. These changes constitute observable transformation pathways that help describe how labor reallocation is reflected in agricultural production, rather than formal causal mediation channels. Accordingly, the following hypothesis is proposed:

H2: *Non-agricultural employment is systematically associated with observable transformation pathways, including mechanization, agricultural structural adjustment, and digital development, which reflect changes in agricultural production organization and technological conditions during labor reallocation.*

2.3. Nonlinear Effects Under Technological Progress and Factor Substitution

While Section 2.2 identifies observable transformation pathways associated with labor reallocation, this section explains why the overall relationship between non-agricultural employment and agricultural carbon emission intensity may be nonlinear and conditional on development-stage factors.

The impact of non-agricultural employment on agricultural carbon emissions exhibits nonlinear characteristics, constrained by the levels of economic development and urbanization. In the early stages of development, although labor outflow occurs, agricultural technology, capital accumulation, and institutional support remain insufficient, and green substitution mechanisms have yet to take shape. Due to financial and technological constraints, smallholders tend to rely on low-efficiency machinery and high-carbon inputs to maintain output, resulting in “factor misallocation” and a “carbon lock-in effect” [69,70]. At this stage, non-agricultural employment may lead to an increase in carbon emissions.

Although the Environmental Kuznets Curve (EKC) is traditionally used to describe the relationship between income growth and environmental pollution, its stage-dependent logic provides useful inspiration for understanding the environmental effects of structural transformation. In this study, the inverted U-shaped relationship between non-agricultural employment and agricultural carbon emission intensity is not interpreted as a direct application of the EKC, but rather as an extension based on factor substitution and biased technological progress. In the early stage of labor reallocation, the decline in agricultural labor supply raises labor costs and induces producers to adopt labor-saving but often energy-intensive inputs, such as machinery, fertilizers, pesticides, and diesel, thereby increasing agricultural carbon emission intensity. As non-agricultural employment deepens, scale operation, land consolidation, digital technologies, precision agriculture, and green machinery gradually improve resource allocation and production efficiency. Technological progress then shifts from primarily labor-saving to both labor-saving and energy-saving, leading to a reduction in carbon emission intensity. Therefore, the nonlinear effect reflects the staged evolution of factor substitution and technological upgrading during agricultural transformation.

However, the pace and effectiveness of this transformation depend on external development conditions. Higher levels of economic development and urbanization may strengthen the connection between labor outflow and capital-intensive agricultural production. In regions where green technologies and low-carbon service systems have not yet fully matured, better economic conditions and urban infrastructure may first accelerate mechanization, energy use, and input substitution, thereby amplifying the emission-

increasing effect of non-agricultural employment before the full emission-reduction potential is realized. Different from H1, which concerns the overall nonlinear relationship between non-agricultural employment and agricultural carbon emission intensity, H3 focuses on whether external development conditions alter the marginal effect of non-agricultural employment. Thus, economic development and urbanization can serve as threshold conditions that change the marginal impact of non-agricultural employment on agricultural carbon emission intensity. Based on this, the following hypothesis is proposed:

H3: *Economic development and urbanization serve as threshold conditions that change the marginal effect of non-agricultural employment on agricultural carbon emission intensity.*

2.4. Regional Spillover Effects Under Spatial Linkages and Technology Diffusion

Agricultural carbon emissions exhibit strong spatial dependence, being influenced not only by local factors but also by technological diffusion and industrial linkages across neighboring regions. The theoretical foundation of this spatial interaction lies in New Economic Geography, which emphasizes agglomeration effects, and spatial spillover theory, which highlights interregional interactions [71,72]. According to these frameworks, factor mobility and knowledge diffusion across regions can generate cross-spatial low-carbon externalities.

Regions with higher levels of non-agricultural employment tend to have first-mover advantages in mechanization, technology adoption, and organizational development. Through channels such as industrial linkages, service outsourcing, and technology diffusion, these regions can transmit low-carbon practices to surrounding areas, forming a “green spillover zone” [73]. Meanwhile, the integration of regional agricultural markets further strengthens this spatial transmission mechanism, as changes in labor structure in one region can influence carbon emissions in neighboring areas through agricultural product circulation, technology sharing, and service extension [74]. The spatial spillovers examined in this study are not merely statistical spatial autocorrelation. They refer to cross-regional influences transmitted through agricultural service outsourcing, machinery sharing, technology diffusion, labor-market linkages, and regional product-market integration. Based on this, the following hypothesis is proposed:

H4: *Non-agricultural employment is associated with significant spatial spillover patterns in agricultural carbon emission intensity, whereby regions with higher levels of non-agricultural employment may be linked to lower carbon emission intensity in neighboring areas through technology diffusion and industrial linkages.*

Drawing on the nonlinear-path and agglomeration-based analytical logic of Wang et al. (2026) [75], this study constructs a theoretical framework linking non-agricultural employment and agricultural carbon emission intensity, as illustrated in Figure 1.

3. Research Design

3.1. Data Sources

Based on data availability and completeness, this study selects panel data from 295 prefecture-level and above cities across 31 provinces in China for the period 2011–2023 (excluding Hong Kong, Macao, and Taiwan). Autonomous prefectures, regions, and leagues with inconsistent statistical calibers are excluded to ensure data reliability, resulting in a prefecture-level panel dataset. The primary data sources include the China Statistical Yearbook, China Rural Management Statistical Annual Report, China Population and Employment Statistical Yearbook, China Agricultural Machinery Industry Yearbook, China Rural Statistical Yearbook, China City Statistical Yearbook, China Regional Statis-

tical Yearbook, prefecture-level artificial intelligence patent data from the National Intellectual Property Administration, and the CSMAR database, as well as various provincial and local statistical yearbooks.

To improve data transparency and reproducibility, the data-processing procedures are briefly summarized as follows. First, city-level administrative units were harmonized according to consistent prefecture-level boundaries, and observations with serious missing information were excluded. Second, variables with occasional missing values were supplemented using official statistical yearbooks, provincial yearbooks, and local statistical bulletins where available; observations that could not be reliably supplemented were removed. Third, monetary variables were adjusted to constant prices using appropriate price indices to ensure intertemporal comparability. Fourth, agricultural carbon emissions were calculated from six input-related sources, including fertilizers, pesticides, agricultural film, diesel, plowing, and irrigation, based on the emission-coefficient method. Detailed variable definitions, data sources, preprocessing procedures, and carbon-emission accounting methods are reported in the Supplementary Materials.

3.2. Variable Selection and Description

Table 1 reports the descriptive statistics of the key variables used in the empirical analysis.

Table 1. Descriptive statistics.

Category	Variable	Mean	Std. Dev.	Min	Max
Dependent Variable	Agricultural Carbon Emission Intensity (ACE, total agricultural carbon emissions/total agricultural output value, kg/10,000 yuan, in logarithmic form)	4.68	1.21	2.94	9.97
Core Explanatory Variable	Non-agricultural Employment Ratio (NE, year-end employment in secondary and tertiary sectors/total year-end employment)	0.69	0.14	0.26	0.99
	Population Size (POP, logarithm of total resident population)	5.82	0.77	2.92	8.07
	Agricultural Patents (PAT, logarithm of patent counts + 1)	4.60	1.56	0.00	8.76
Control Variables	Agricultural Structure (AGS, grain sown area/total crop sown area)	0.68	0.23	0.33	0.94
	Farm Size (LAS, cultivated land per capita, mu)	0.65	0.44	0.09	1.85
	Agricultural Industrial Structure (AIS, agricultural output value/total output of agriculture, forestry, animal husbandry, and fishery)	0.52	0.12	0.03	0.89
	Agricultural Mechanization Level (MEC, total agricultural machinery power, 10 ⁶ kW)	3.25	3.23	0.94	14.61
	Digitalization Level (AI, logarithm of AI patent counts + 1)	4.65	2.02	0.00	11.64
	Economic Development Level (GDP, GDP per capita, 10,000 yuan)	5.85	3.72	0.62	31.29
Mechanism Variables	Government Intervention (GOV, general public budget expenditure/GDP)	0.22	0.14	0.05	1.64
	Urbanization Level (URB, non-agricultural population/registered population)	0.564	0.149	0.14	1.00

Source: calculated by the authors based on the dataset described in Section 3.1.

The definitions, calculation methods, and processing procedures of all variables are reported in Table S1 in the Supplementary Materials.

The selected control variables capture demographic, technological, structural, economic, and institutional factors that may affect agricultural carbon emission intensity. Agricultural subsidies and climatic factors are not included separately because consistent long-term data at the prefecture-level city scale are difficult to obtain. To mitigate this concern, city fixed effects are used to control for time-invariant geographical and climatic characteristics, while year fixed effects absorb common macroeconomic, policy, and climate shocks.

3.2.1. Dependent Variable: Agricultural Carbon Emission Intensity

Given the substantial differences in agricultural production scales across cities, measuring emissions solely by total agricultural carbon emissions may lead to biased comparisons. Therefore, this study adopts agricultural carbon emission intensity as the dependent variable. Following Li et al. (2011) [76], Gong et al. (2020) [77], and Xu et al. (2026) [78], agricultural carbon emissions are calculated using the widely applied emission coefficient method. Specifically, emissions are estimated from six major sources: the use of chemical fertilizers, pesticides, and agricultural film, as well as diesel consumption, plowing, and irrigation. The corresponding emission coefficients are 0.89, 4.93, 5.18, 0.59, 266.48, and 312.6, respectively. These coefficients are drawn from widely used agricultural carbon-accounting studies in China and are consistent with the input-based accounting framework adopted in the IPCC guidelines and related domestic studies. This method provides a consistent and comparable framework for estimating emissions from major agricultural production inputs. The calculation model is specified as follows:

Formula for Agricultural Carbon Emissions:

$$C_{it} = \sum C_{nit} = \sum T_{nit} \times \sigma_n \quad (1)$$

where C_{it} denotes the total agricultural carbon emissions of city i in year t , C_{nit} represents the carbon emissions from the n -th source, T_{nit} refers to the quantity of each emission source, and σ_n denotes the corresponding emission coefficient.

The detailed carbon emission accounting framework and emission coefficients are reported in Supplementary Section S2 of the Supplementary Materials.

Formula for Agricultural Carbon Emission Intensity:

$$Ace_{it} = \frac{C_{it}}{GEP_{it}} \quad (2)$$

where Ace_{it} denotes agricultural carbon emission intensity, C_{it} represents total agricultural carbon emissions, and GEP_{it} refers to the total agricultural output value; i indexes cities and t denotes time. In the descriptive statistics and empirical regressions, ACE is reported and used in logarithmic form to reduce skewness and improve the comparability of agricultural carbon emission intensity across cities.

It should be noted that the carbon-emission inventory employed in this study mainly focuses on emissions associated with agricultural production inputs. Due to data limitations, methane emissions from rice cultivation, enteric fermentation, and livestock waste management are not directly included. Therefore, the estimated emissions should be interpreted as partial measures of agricultural greenhouse-gas emissions rather than a complete agricultural GHG inventory. To reduce concerns about coefficient selection and accounting boundaries, this study further conducts robustness checks by excluding major rice-producing regions and livestock-intensive regions, where methane-related emissions may be more important. The main nonlinear relationship remains qualitatively unchanged.

3.2.2. Core Explanatory Variable: Non-Agricultural Employment Ratio

The non-agricultural employment ratio (NE) is measured as the share of employment in the secondary and tertiary industries in total employment at the end of each year at the prefecture-level city scale. This indicator reflects the sectoral employment structure of each city rather than individual-level migration flows. Therefore, it does not directly identify migrant workers or distinguish their origin and destination at the household level. Nevertheless, because consistently measured city-level migrant-flow data are difficult to obtain for the full sample period, this stock-based employment-structure indicator provides a comparable measure of the cumulative degree of labor reallocation from agriculture to non-agricultural sectors. Accordingly, the empirical results should be interpreted

as evidence on the relationship between the level of non-agricultural employment and agricultural carbon emission intensity, rather than as direct evidence on annual labor migration flows.

3.3. Model Specification and Construction

3.3.1. Baseline Regression Model

To examine the nonlinear relationship between non-agricultural employment and agricultural carbon emission intensity, this study specifies the following baseline fixed-effects model:

$$Ace_{it} = \beta_0 + \beta_1 NE_{it} + \beta_2 NE_{it}^2 + \gamma X + \mu_i + \varepsilon_{it} \quad (3)$$

where Ace_{it} denotes agricultural carbon emission intensity, NE_{it} represents the non-agricultural employment ratio, NE_{it}^2 captures the potential nonlinear effect. X is a vector of control variables, including digitalization, economic development level, urbanization level, government intervention, and agricultural structure. μ_i captures individual fixed effects, and ε_{it} is the error term. β_0 is the constant term, while β_1 and β_2 are coefficients to be estimated. Subscripts i and t denote city and year, respectively.

3.3.2. Potential Pathway Analysis

To further explore the potential pathways associated with the impact of non-agricultural employment on agricultural carbon emission intensity, this study examines three factors that are closely related to agricultural transformation: agricultural mechanization (MEC), agricultural structure adjustment (AGS), and agricultural digitalization (AI). These factors reflect important changes in factor allocation, production organization, and technological upgrading during the process of rural labor transfer.

As rural labor shifts toward non-agricultural sectors, agricultural producers may adjust production structures, modify machinery utilization, and increasingly adopt digital technologies to maintain production efficiency. Therefore, examining the relationship between non-agricultural employment and these variables helps describe the potential pathways through which labor reallocation may be associated with agricultural production patterns and environmental outcomes.

The empirical model is specified as follows:

$$M_{it} = \alpha_0 + \alpha_1 NE_{it} + \alpha_2 NE_{it}^2 + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where M_{it} represents the potential mechanism variable, including agricultural mechanization (MEC), agricultural structure (AGS), and agricultural digitalization (AI). NE_{it} represents the non-agricultural employment ratio; NE_{it}^2 captures the potential nonlinear effect. X_{it} denotes the set of control variables. μ_i and λ_t represent city fixed effects and year fixed effects, respectively, while ε_{it} is the random error term.

The analysis focuses on whether non-agricultural employment is systematically associated with changes in agricultural mechanization, production structure, and digital development, thereby providing exploratory evidence on potential pathways linking labor transfer and agricultural carbon emissions.

3.3.3. Threshold Model

Considering the potential nonlinear effects of urbanization on agricultural carbon emissions, a panel threshold model following Hansen (1999) [79] is employed. Taking a single-threshold case as an example:

$$Ace_{it} = u_i + \beta_1 X + \beta_2 NE_{it} \times I(URB_{it} \leq \gamma) + \beta_3 NE_{it} \times I(URB_{it} > \gamma) + \varepsilon_{it} \quad (5)$$

where u_i represents individual effects, X is a vector of control variables, URB_{it} is the threshold variable, γ is the estimated threshold value, $I(\cdot)$ is an indicator function, and ε_{it} is the error term.

3.3.4. Spatial Econometric Model

To test Hypothesis 4 regarding spatial spillover effects, a Spatial Durbin Model (SDM) is constructed following Xu et al. (2022) [80] and Ding et al. (2022) [81]:

$$Ace_{it} = \rho \times W \times Ace_{it} + \lambda_1 NE_{it} + \beta X_{it} + \lambda_2 \times W \times NE_{it} + \eta W X_{it} + \kappa_i + v_t + \varepsilon_{it} \quad (6)$$

where ε_{it} is the idiosyncratic error term, μ_i denotes city fixed effects, and λt denotes year fixed effects. The model includes spatial fixed effects κ_i and time fixed effects v_t . Subscripts i, j , and t denote city i , city j , and year t , respectively. ρ is the spatial autoregressive coefficient. In the baseline specification, W is constructed as a binary contiguity matrix. Specifically, $W_{ij} = 1$ if city i and city j share a common administrative boundary, and $W_{ij} = 0$ otherwise. The diagonal elements are set to zero, and the matrix is row-standardized before estimation. This matrix is used because the study focuses on local spatial interactions transmitted through neighboring agricultural service markets, machinery sharing, labor-market linkages, and technology diffusion. To examine whether the spatial results are sensitive to the choice of W , two alternative matrices are also used in the robustness analysis: an inverse distance-squared matrix based on geographic distance between cities and an economic-distance matrix based on differences in economic development levels.

The estimated effects of non-agricultural employment on agricultural carbon emission intensity are decomposed into direct, indirect, and total effects, defined as $f_{ii}(W) = \frac{\partial Ace_{ij}}{\partial NE_{im}}$, $f_{ij}(W) = \frac{\partial Ace_{ij}}{\partial NE_{jm}}$ and $Total = f_{ii}(W) + f_{ij}(W)$, respectively, where the indirect effect captures the spatial spillover effect.

4. Empirical Analysis

4.1. Trend Analysis

Based on the estimation of average data from 31 provinces in China over the period 2011–2023, agricultural carbon emission intensity and the share of non-agricultural employment exhibit a clear pattern of coordinated evolution. During the study period, agricultural carbon emission intensity declined steadily from 255.92 in 2011 to 89.02 in 2023, representing a cumulative decrease of 65.21%. Specifically, the period from 2011 to 2016 was characterized by a relatively slow decline, with an average annual reduction of approximately 4.76%, whereas from 2017 to 2023 the decline accelerated, with the average annual rate increasing to 8.94%. Notably, a strong downward trend was maintained during 2020–2023.

In contrast, the share of non-agricultural employment showed a steady upward trend, rising from 66.31% in 2011 to 77.03% in 2023, an increase of 10.72 percentage points. As illustrated in Figure 2, agricultural carbon emission intensity declined while the non-agricultural employment ratio increased during the sample period. This inverse movement indicates a descriptive pattern of co-evolution between employment-structure transformation and agricultural carbon intensity reduction. However, the trend comparison alone does not establish a causal relationship. Whether non-agricultural employment is associated with changes in agricultural carbon emission intensity, and through which mechanisms this relationship may operate, is examined in the subsequent econometric analysis.

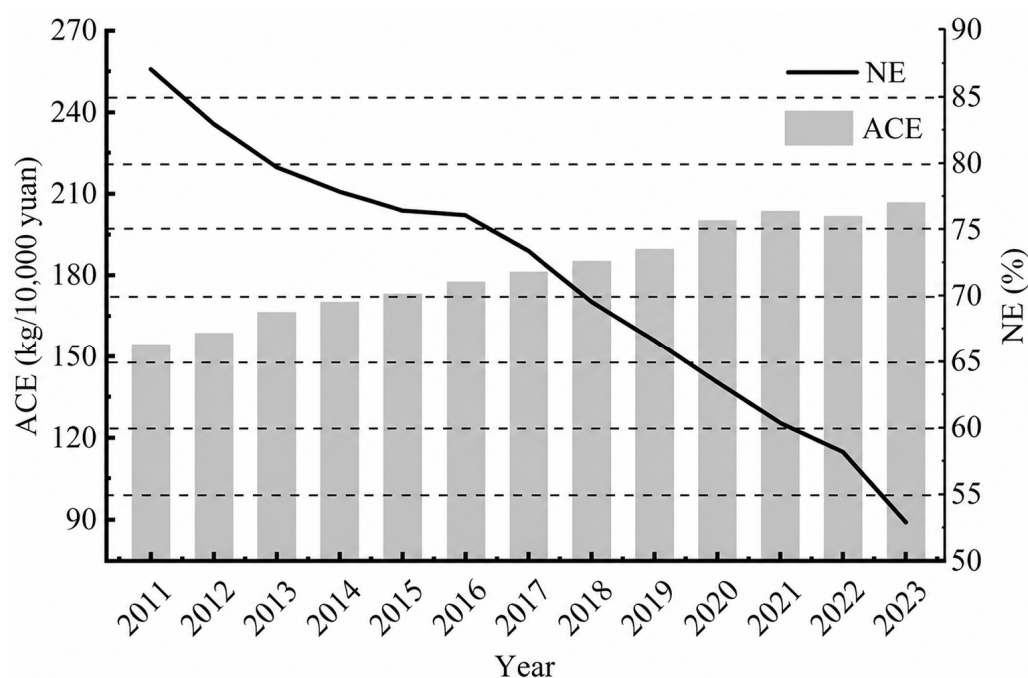


Figure 2. Trends in Agricultural Carbon Emission Intensity and the Non-Agricultural Employment Ratio in China, 2011–2023. Source: calculated and plotted by the authors using Origin based on the dataset described in Section 3.1.

4.2. Baseline Regression Results

The baseline regression results based on Model (3) are reported in Table 2. The effect of the non-agricultural employment ratio on agricultural carbon emission intensity exhibits a significant nonlinear pattern. In the linear specifications (Columns 1 and 3), the coefficient of NE is significantly positive, indicating that in the initial stage of labor outflow, agricultural production relies more heavily on high-carbon inputs—such as mechanization and chemical fertilizers—to compensate for labor shortages, thereby increasing carbon emission intensity.

However, after introducing the quadratic term (Columns 2 and 4), the coefficient of the linear term remains significantly positive, while the coefficient of the squared term becomes significantly negative, revealing a typical inverted U-shaped relationship. This suggests that non-agricultural employment initially increases emissions, but as its level rises further, the expansion of scale operations, improved resource allocation, and the adoption of green technologies gradually shift agricultural production from an extensive to an intensive and low-carbon mode, leading to a decline in carbon emission intensity.

The inclusion of control variables improves the explanatory power of the model, with the R^2 increasing from 0.61 to 0.64. The inverted U-shaped relationship remains statistically significant after controlling for observed covariates as well as city and year fixed effects. This suggests that the estimated nonlinear association is stable within the fixed-effects framework, although potential time-varying omitted factors cannot be completely ruled out. Overall, the results suggest that the estimated relationship between non-agricultural employment and agricultural carbon emission intensity is not monotonically increasing, but follows a dynamic pattern of “increase followed by decline,” thereby supporting Hypothesis H1.

Table 2. Results of baseline regression.

Variables	(1)	(2)	(3)	(4)
NE	0.511 *** (8.66)	2.656 *** (10.24)	0.419 *** (7.22)	2.188 *** (8.29)
NE ²		−1.718 *** (−8.48)		−1.409 *** (−6.87)
Constant term	2.186 *** (56.51)	1.558 *** (18.71)	2.737 *** (19.39)	2.046 *** (11.86)
Control Variables	No	No	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	3835	3835	3835	3835
R ²	0.61	0.62	0.63	0.64

Note: *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. t-values are reported in parentheses. Source: estimated by the authors using Stata 16.0.

To further assess the validity and policy relevance of the estimated nonlinear relationship, the turning point implied by the quadratic specification was calculated. Based on the estimated coefficients in the full specification, the turning point of the non-agricultural employment ratio is 0.736, with a 95% confidence interval of 0.640–0.833. This value falls within the observed sample range, indicating that the inverted U-shaped relationship is economically meaningful rather than being driven by an out-of-sample turning point. Approximately 40.6% of the city-year observations are located above this turning point, suggesting that a substantial proportion of prefecture-level cities may have already entered the descending segment of the curve, where further increases in non-agricultural employment are associated with lower agricultural carbon emission intensity. This result provides useful evidence for identifying the development stage of different cities and designing stage-specific agricultural carbon-reduction policies.

4.3. Potential Pathway Analysis

4.3.1. Potential Pathway Results

Table 3 reports the results of the potential pathway analysis with a nonlinear specification. To ensure consistency with the baseline model, both NE and NE² are included in the pathway equations. The results show that non-agricultural employment is significantly and nonlinearly associated with agricultural mechanization, agricultural structure adjustment, and agricultural digitalization.

For agricultural mechanization, the coefficient of NE is significantly positive, while the coefficient of NE² is significantly negative, indicating an inverted U-shaped association. This suggests that, in the early stage of labor reallocation, agricultural producers may increase machinery use to substitute for labor shortages. However, as non-agricultural employment reaches a higher level, the expansion of traditional machinery inputs may weaken, possibly because production becomes more service-oriented, efficiency-oriented, and digitally supported.

For agricultural structure adjustment, the coefficient of NE is significantly negative, whereas the coefficient of NE² is significantly positive, suggesting a U-shaped association. This result indicates that labor reallocation is accompanied by changes in cropping structure and production organization. At higher levels of non-agricultural employment, scale operation, mechanized services, and policy support may further reshape the agricultural production structure.

For agricultural digitalization, both NE and NE² are significantly positive, suggesting that non-agricultural employment is positively and increasingly associated with AI-re-

lated patenting activity and local digital innovation capacity. This indicates that cities with higher levels of non-agricultural employment may have stronger technological foundations and greater potential for agricultural digital transformation.

Overall, these findings suggest that non-agricultural employment is systematically associated with transformation-related variables, including mechanization, agricultural structure adjustment, and digital development. The results provide exploratory evidence on potential pathways linking labor reallocation and agricultural carbon emission intensity, but they should not be interpreted as formal evidence of causal mediation.

Table 3. Potential Pathway Analysis.

Variables	MEC	AGS	AI
NE	1.215 *** (11.42)	−0.714 *** (−13.29)	1.118 *** (21.36)
NE ²	−2.182 *** (−4.13)	1.394 *** (15.36)	0.935 *** (25.52)
Constant term	0.580 *** (9.43)	−0.831 *** (−9.07)	0.471 *** (6.11)
Control Variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Note: *** denotes statistical significance at the 1% level. t-values are reported in parentheses. Source: estimated by the authors using Stata 16.0.

4.3.2. Threshold Effect of Economic Development Level and Urbanization

To further examine whether the marginal association between non-agricultural employment and agricultural carbon emission intensity varies across development stages, this study employs the panel threshold regression method developed by Hansen (1999) [79]. The results are reported in Table 4.

Panel A of Table 4 reports the threshold effect test results. When economic development is used as the threshold variable, the single-threshold effect is statistically significant at the 1% level, with an estimated threshold value of 3.9558, a 95% confidence interval of 3.9137–3.9748, an F-value of 333.83, and a bootstrap *p*-value of 0.000. When urbanization is used as the threshold variable, the single-threshold effect is also statistically significant, with an estimated threshold value of 0.4806, a 95% confidence interval of 0.4790–0.4814, an F-value of 178.46, and a bootstrap *p*-value of 0.0133. These results indicate that the relationship between non-agricultural employment and agricultural carbon emission intensity varies across different stages of economic development and urbanization.

Panel B of Table 4 further reports the regime-specific coefficients of non-agricultural employment. For the economic development threshold, the coefficient of NE is 1.337 when GDP is below or equal to 3.9558 and 1.587 when GDP exceeds 3.9558, with both estimates statistically significant at the 1% level. This suggests that the positive association between non-agricultural employment and agricultural carbon emission intensity becomes stronger after the level of economic development crosses the estimated threshold.

For the urbanization threshold, the coefficient of NE is 1.564 when URB is below or equal to 0.4806 and 1.716 when URB exceeds 0.4806, with both estimates statistically significant at the 1% level. This indicates that urbanization also strengthens the marginal association between non-agricultural employment and agricultural carbon emission intensity.

These findings suggest that economic development and urbanization condition the marginal association between non-agricultural employment and agricultural carbon emission intensity. Specifically, the positive association between non-agricultural employment and agricultural carbon emission intensity becomes stronger after economic development

or urbanization crosses the estimated threshold. This may reflect the fact that, in more developed or more urbanized regions, agricultural production systems may become more capital-intensive and input-intensive before green agricultural technologies and low-carbon service systems are sufficiently mature.

It should be noted that the threshold results should not be interpreted as an additional test of the inverted U-shaped relationship identified in the baseline quadratic model. The baseline model examines the overall nonlinear relationship between non-agricultural employment and agricultural carbon emission intensity, whereas the threshold model examines whether development-stage conditions alter the marginal association between non-agricultural employment and agricultural carbon emission intensity. Therefore, the threshold analysis complements the baseline model by identifying boundary conditions under which the NE–ACE relationship becomes stronger or weaker.

Overall, the results support H3 by showing that economic development and urbanization serve as threshold conditions that change the marginal association between non-agricultural employment and agricultural carbon emission intensity.

Table 4. Threshold Effect Test Results and Regime-Specific Coefficients.

Panel A. Threshold Effect Test Results									
Threshold Variable	Model	Threshold Value	95% CI	F-Value	p-Value	Bootstrap	Critical Values		
							0.1	0.05	0.01
GDP	Single Threshold	3.9558	[3.9137, 3.9748]	333.83	0.000	300	104.90	118.94	153.70
URB	Single Threshold	0.4806	[0.4790, 0.4814]	178.46	0.0133	300	121.64	141.61	179.16
Panel B. Regime-Specific Coefficients of NE									
Threshold Variable	Regime		Coefficient of NE		t-Value		Significance		
GDP	GDP ≤ 3.9558		1.337 ***		21.24		1%		
GDP	GDP > 3.9558		1.587 ***		27.24		1%		
URB	URB ≤ 0.4806		1.564 ***		24.71		1%		
URB	URB > 0.4806		1.716 ***		29.04		1%		

Note: *** denotes statistical significance at the 1% level. Bootstrap replications are 300. Panel A reports the threshold effect test results, while Panel B reports the regime-specific coefficients of non-agricultural employment before and after each threshold. Source: estimated by the authors using Stata 16.0.

4.4. Endogeneity Concerns and Supplementary Robustness Check

Although the fixed-effects specification controls for time-invariant city characteristics and common year shocks, potential endogeneity arising from reverse causality, omitted time-varying factors, and measurement error cannot be fully ruled out. For example, regions with higher levels of economic development, better infrastructure, stronger technological capacity, or more advanced agricultural service systems may simultaneously exhibit higher non-agricultural employment and different levels of agricultural carbon emission intensity. Therefore, the estimated coefficients should be interpreted with caution.

To provide supplementary evidence, this study uses lagged non-agricultural employment as an instrumental variable and conducts an instrumental-variable estimation. The rationale is that past employment structure is strongly correlated with current non-agricultural employment. The first-stage results indicate that the lagged variable is highly correlated with current non-agricultural employment, and the weak-instrument statistic is far above the conventional critical value, suggesting that the instrument is relevant.

However, instrument relevance does not guarantee the validity of the exclusion restriction. Lagged non-agricultural employment may still be correlated with unobserved development conditions that also affect agricultural carbon emission intensity. Therefore,

the instrumental-variable results are interpreted only as supplementary robustness evidence rather than as definitive causal identification.

As shown in Table 5, the estimated association between non-agricultural employment and agricultural carbon emission intensity remains statistically significant in the instrumental-variable specification. This provides additional evidence that the main empirical relationship is not entirely driven by weak instrument concerns. Nevertheless, because the exclusion restriction cannot be fully verified, this study avoids making strong causal claims. The results are therefore interpreted as robust conditional associations rather than fully identified causal effects.

It should also be noted that the IV specification focuses on the linear association involving NE and does not fully reproduce the quadratic baseline specification. Therefore, the IV results are used only to assess the stability of the main association and should not be interpreted as direct IV evidence for the inverted U-shaped relationship.

Table 5. Supplementary Instrumental-Variable Results.

Variables	First Stage	Second Stage
Lagged NE	0.96 *** (299.00)	
NE		2.16 *** (15.83)
Control Variables	Yes	Yes
FE	Yes	Yes
Under-identification Test	1314.368 ***	
Weak Identification Test	820.04 [16.3800]	
N	3835	3835

Note: *** denotes statistical significance at the 1% level. Values in [] represent the Stock–Yogo critical value at the 10% significance level. The instrumental-variable results are reported as supplementary robustness evidence. A high first-stage F-statistic indicates instrument relevance but does not by itself verify the exclusion restriction. Source: estimated by the authors using Stata 16.0.

The IV estimates provide supplementary evidence that the positive association between non-agricultural employment and agricultural carbon emission intensity remains stable. However, because the IV specification does not fully reproduce the quadratic baseline model, it should be interpreted only as a robustness check rather than direct evidence for the inverted U-shaped relationship.

4.5. Robustness Tests

To ensure the robustness of the empirical results, several additional tests are conducted. First, HC is used as an alternative proxy for non-agricultural employment, measured by the ratio of students enrolled in higher education institutions to the total population at year-end; a higher value indicates a stronger tendency toward non-agricultural employment. Second, to mitigate the influence of outliers, all variables—including the dependent variable, core explanatory variable, and control variables—are winsorized at the 1% level. Third, considering that provincial capitals and municipalities directly under the central government may differ significantly from other prefecture-level cities in terms of economic, social, cultural, and policy environments, these special samples (i.e., Beijing, Tianjin, Shanghai, Chongqing, and 26 provincial capitals) are excluded to eliminate potential bias. In addition, considering that the agricultural carbon-emission inventory used in this study mainly focuses on input-related emissions, two sensitivity tests related to carbon-accounting boundaries are conducted. Fourth, to assess whether the omission of methane emissions from rice cultivation affects the results, major rice-producing regions

are excluded from the sample. Fifth, to evaluate the influence of methane emissions from livestock production, livestock-intensive regions are excluded from the sample.

As shown in Table 6, the robustness tests provide additional support for the stability of the main findings from different perspectives. The alternative-variable test, winsorization test, and exclusion of special samples show that the estimated relationship remains statistically significant when the measurement of non-agricultural employment, the influence of outliers, and the role of special cities are considered. These results suggest that the main relationship is not driven by variable selection, extreme values, or the inclusion of provincial capitals and municipalities. In addition, to directly examine the robustness of the nonlinear specification and to address the possible omission of methane-related emissions, this study further excludes major rice-producing regions and livestock-intensive regions. In both subsamples, the coefficient of NE remains significantly positive, while the coefficient of NE² remains significantly negative. This indicates that the inverted U-shaped relationship remains robust after excluding regions where methane emissions from rice cultivation or livestock production may be relatively important.

Table 6. Robustness Test Results.

Variables	Alternative Variable	Winsorization	Excluding Special	Excluding Rice-Pro-	Excluding Livestock-In-
	ACE	ACE	Samples ACE	ducing Regions ACE	tensive Regions ACE
HC	−6.51 *** (−15.21)				
NE		−0.99 *** (−15.45)	−0.79 *** (−10.94)	3.007 *** (3.69)	2.394 *** (3.25)
NE ²				−2.021 *** (−3.16)	−1.572 *** (−2.73)
Control Variables	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
Constant term	−1.38 *** (−17.86)	−0.68 *** (−6.76)	−1.36 *** (−12.73)	0.606 (0.81)	2.212 *** (3.36)
R ²	0.56	0.55	0.61	0.977	0.959
N	3835	3835	3445	2145	3354

Note: *** denotes statistical significance at the 1% level. Columns (1)–(3) report general robustness checks based on alternative variable measurement, winsorization, and sample exclusion. Columns (4)–(5) report nonlinear sensitivity tests including both NE and NE². Source: estimated by the authors using Stata 16.0.

4.6. Heterogeneity Analysis

The regression results in Table 7 reveal significant heterogeneity in the impact of non-agricultural employment on agricultural carbon emission intensity across different resource endowments. In regions with low arable land endowment, the coefficient of the non-agricultural employment ratio is 0.525 and statistically significant at the 1% level, indicating that labor outflow significantly increases agricultural carbon intensity. In contrast, in regions with high arable land endowment, the coefficient is −0.020 and statistically insignificant, suggesting that abundant land resources can weaken or even offset the emission-increasing effect of non-agricultural employment. The Fisher test ($p = 0.000$) further confirms the presence of systematic differences between the two groups, highlighting the strong linkage between land endowment and labor mobility patterns.

Specifically, in low-land regions, binding resource constraints lead farmers to adopt labor-saving but energy-intensive small-scale mechanization following labor outflow. Limited capital accumulation and technological capacity further hinder the adoption of

green machinery and low-carbon inputs, resulting in a “resource constraint–technology lock-in” effect, whereby carbon intensity rises with increasing non-agricultural employment. In contrast, high-land regions benefit from economies of scale and specialized operations, enabling the adoption of energy-efficient machinery and optimized factor allocation, thereby creating a “technological buffering” effect that stabilizes or mitigates carbon emission pressures.

Further subgroup analysis between major grain-producing regions and non-major grain-producing regions shows that the coefficient for major grain-producing areas is significantly positive, indicating that these regions are more likely to remain on the upward segment of the inverted U-shaped curve. A possible explanation is that major grain-producing regions undertake important national food-security responsibilities, which requires them to maintain stable grain output and relatively rigid cropping structures. Under labor outflow, these regions may rely more heavily on machinery, fertilizers, pesticides, and diesel to stabilize production, thereby strengthening the emission-increasing effect of non-agricultural employment. In addition, agricultural support policies and mechanization subsidies aimed at ensuring grain production may further encourage capital- and input-intensive production modes before green machinery and low-carbon technologies are fully adopted. As a result, the transition from labor-saving but energy-intensive substitution to energy-saving technological upgrading may be slower in major grain-producing regions, making it more difficult for these regions to reach the emission-reduction segment of the inverted U-shaped curve.

It should be noted that the grouping variables used in the heterogeneity analysis may not be completely exogenous. However, arable land endowment and major grain-producing status in China are largely determined by relatively stable natural conditions, historical agricultural patterns, and national food-security policies. Therefore, their potential endogeneity is expected to be limited, and they remain useful dimensions for examining regional heterogeneity.

Table 7. Heterogeneity Analysis Results.

Variables	Low-Arable-Land Regions	High-Arable-Land Regions	Major Grain-Producing Regions	Non-Major Grain-Producing Regions
NE	0.525 *** (3.24)	−0.020 (0.163)	0.301 *** (2.71)	0.304 * (1.82)
Constant term	4.776 *** (10.38)	5.031 *** (13.86)	4.555 *** (12.24)	5.001 *** (13.52)
Control Variables	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
R ²	0.542	0.646	0.585	0.626
N	1918	1917	2210	1625

Note: * and *** denote statistical significance at the 10% and 1% levels, respectively. t-values are reported in parentheses. Source: estimated by the authors using Stata 16.0.

To further exploit the prefecture-level nature of the dataset and respond to the need for more refined heterogeneity analysis, this study additionally divides the sample into urban-agglomeration cities and non-urban-agglomeration cities. The results are reported in Table 8.

Table 8. Heterogeneity Analysis by Urban Agglomeration Status.

Variables	Urban Agglomerations	Non-Urban Agglomerations
NE	−0.244 (−0.29)	3.005 *** (4.02)

NE ²	0.279 (0.42)	−2.036 *** (−3.38)
Control Variables	Yes	Yes
FE	Yes	Yes
R ²	0.977	0.966
N	1014	2821

Note: *** denotes statistical significance at the 1% level. t-values are reported in parentheses. Source: estimated by the authors using Stata 16.0.

In urban-agglomeration cities, the coefficients of NE and NE² are statistically insignificant, suggesting that the nonlinear effect of non-agricultural employment on agricultural carbon emission intensity is relatively weak. This may be because urban-agglomeration cities usually have stronger infrastructure, more developed agricultural producer services, and faster diffusion of green and digital technologies. These conditions may weaken the emission-increasing effect caused by labor outflow and accelerate the transition toward low-carbon production.

In contrast, in non-urban-agglomeration cities, the coefficient of NE is significantly positive, while the coefficient of NE² is significantly negative, indicating a significant inverted U-shaped relationship. This suggests that non-urban-agglomeration cities are more likely to experience a staged process in which labor outflow first induces carbon-intensive substitution through machinery, fertilizers, pesticides, and diesel, and then gradually promotes emission reduction as scale operation and technological upgrading advance. These findings indicate that the carbon effect of non-agricultural employment is strongly shaped by spatial development conditions and further support the necessity of differentiated regional policies.

4.7. Spatial Effect Analysis

To identify the interregional transmission mechanism of non-agricultural employment, this study further incorporates a Spatial Durbin Model (SDM) to examine its spatial spillover effects on agricultural carbon emission intensity in neighboring regions.

A binary contiguity (0–1) spatial weight matrix is employed to calculate Moran’s I, where adjacent spatial units are assigned a weight of 1 and 0 otherwise. The Global Moran’s I results for agricultural carbon emission intensity from 2011 to 2023 are reported in Table 9. The Moran’s I statistics for all variables indicate a strong spatial clustering pattern. As robustness checks, an inverse distance-squared matrix and an economic-distance matrix are also applied; however, the contiguity matrix is more consistent with this study’s focus on local spatial interactions.

Table 9. Global Moran’s I of Agricultural Carbon Emission Intensity in Chinese Cities, 2011–2023.

Year	2011	2012	2013	2014	2015	2016	2017
Moran’s I	0.338 ***	0.340 ***	0.340 ***	0.341 ***	0.345 ***	0.345 ***	0.360 ***
Year	2018	2019	2020	2021	2022	2023	
Moran’s I	0.347 ***	0.351 ***	0.351 ***	0.342 ***	0.329 ***	0.290 ***	

Note: *** denotes statistical significance at the 1% level. Source: calculated by the authors using Stata 16.0 based on the dataset described in Section 3.1.

Based on the results in Table 9, agricultural carbon emission intensity across the 295 cities exhibits significant positive spatial autocorrelation at the 1% level throughout 2011–2023, indicating strong spatial dependence among regions. Furthermore, Moran’s I values show an overall declining trend over time, suggesting a gradual weakening of spatial dependence. This pattern may reflect the implementation of low-carbon policies, which have

accelerated emission reductions in high-emission regions and contributed to convergence in regional emission levels.

To obtain more accurate parameter estimates, it is necessary to incorporate a spatial weight matrix and apply spatial econometric methods [80,81] Table 10 presents the ordinary least squares (OLS) regression results for non-agricultural employment along with the corresponding Lagrange Multiplier (LM) tests. Both the LM test and the robust LM test are significant at the 1% level, indicating the presence of both spatial error dependence and spatial lag dependence. Therefore, the null hypothesis of a pooled panel model is rejected, and the Spatial Durbin Model is ultimately selected as the appropriate estimation approach.

Table 10. Spatial Dependence Tests.

Test Method	Statistic	p-value
LM test no spatial error	1748.173 ***	0.000
Robust LM test no spatial error	929.451 ***	0.000
LM test no spatial lag	849.294 ***	0.000
Robust LM test no spatial lag	15.338 ***	0.000

Note: *** denotes statistical significance at the 1% level. Source: estimated by the authors using Stata 16.0.

The spatial effect decomposition results are reported in Table 11. Under the baseline contiguity matrix, the direct effect of non-agricultural employment is significantly positive, whereas the coefficient of its quadratic term is significantly negative. Similar patterns are observed for both the indirect effect and the total effect. These findings indicate that non-agricultural employment exerts a significant inverted U-shaped influence on agricultural carbon emission intensity not only within a region but also through spatial spillover channels.

Specifically, in the early stages of labor transfer, the expansion of non-agricultural employment may increase agricultural carbon emission intensity through greater reliance on machinery and production inputs. However, as labor transfer deepens, improvements in factor allocation, scale operation, and technological upgrading gradually dominate, leading to reductions in agricultural carbon emission intensity. Moreover, these effects extend beyond local boundaries and generate significant spatial spillovers across neighboring regions.

The spatial autoregressive coefficient (ρ) is significantly positive, indicating strong spatial dependence in agricultural carbon emission intensity among cities. Therefore, neglecting spatial interactions would underestimate the broader regional effects of labor transfer on agricultural carbon emissions.

Table 11. Spatial Durbin Model Results under Alternative Spatial Weight Matrices.

Effect	Variable	Contiguity Matrix	Distance Matrix	Economic Matrix
Direct Effect	NE	1.126 *** (4.31)	0.752 *** (2.83)	2.177 *** (8.30)
	NE ²	−0.773 *** (−3.84)	−0.502 ** (−2.46)	−1.475 *** (−7.21)
Indirect Effect	NE	3.707 *** (7.09)	49.970 *** (3.28)	1.744 *** (2.44)
	NE ²	−2.528 *** (−5.98)	−36.021 *** (−3.23)	−0.938 * (−1.68)
Total Effect	NE	4.833 *** (8.37)	48.722 *** (3.33)	3.921 *** (5.11)

	NE ²	−3.301 *** (−7.08)	−36.523 *** (−3.27)	−2.413 *** (−4.02)
Spatial coefficient (ρ)		0.292 *** (13.91)	0.651 ***	0.052 ***

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. z-values/t-values are reported in parentheses. Source: estimated by the authors using Stata 16.0.

It should be noted that the direct effect estimated by the Spatial Durbin Model is qualitatively consistent with the baseline fixed-effects results: the coefficient of NE is positive, while the coefficient of NE² is negative. This indicates that the inverted U-shaped relationship remains valid after accounting for spatial dependence. Compared with the baseline model, the SDM further decomposes the effect into local and spillover components, showing that non-agricultural employment affects not only local agricultural carbon emission intensity but also that of neighboring regions through spatial interaction channels. Therefore, the spatial model does not contradict the baseline results; rather, it provides a more complete interpretation of the nonlinear relationship by incorporating interregional dependence.

To further evaluate the robustness of the spatial econometric results, two alternative spatial weighting matrices, namely an inverse-distance matrix and an economic weighting matrix, were employed. As reported in Table 11, the estimated direct, indirect, and total effects remain qualitatively consistent across the three spatial weighting matrices. In all specifications, the coefficient of NE remains significantly positive, whereas the coefficient of NE² remains significantly negative, indicating that both the local effect and the spatial spillover effect continue to follow an inverted U-shaped pattern. These results suggest that the identified nonlinear spatial relationship is not driven by a particular spatial weighting specification.

5. Discussion

Based on panel data from 295 prefecture-level cities in China from 2011 to 2023, this study examines the nonlinear, threshold, heterogeneous, and spatial associations between non-agricultural employment and agricultural carbon emission intensity. The findings provide several insights that can be discussed in relation to the existing literature.

First, this study identifies a significant inverted U-shaped relationship between non-agricultural employment and agricultural carbon emission intensity. This finding is broadly consistent with studies showing that rural labor transfer and off-farm employment can influence agricultural environmental performance through factor reallocation, land transfer, and changes in production organization. However, unlike studies that mainly assume a linear relationship between labor transfer and agricultural carbon emissions, our results suggest that the relationship between non-agricultural employment and agricultural carbon emission intensity is stage-dependent. In the early stage, labor outflow may induce farmers to rely more heavily on machinery, fertilizers, pesticides, and diesel to compensate for labor shortages, thereby increasing carbon emission intensity. In the later stage, scale operation, land consolidation, green technologies, and improved resource allocation gradually dominate, leading to a reduction in carbon emission intensity. Therefore, the inverted U-shaped relationship reflects the dynamic transition from labor-saving but carbon-intensive substitution to low-carbon technological upgrading.

Second, the pathway analysis suggests that non-agricultural employment is associated with changes in agricultural mechanization, agricultural structure, and digital development. This result echoes existing studies emphasizing the roles of mechanization, digital agriculture, and production-service outsourcing in reshaping agricultural production and environmental outcomes. At the same time, our findings indicate that these pathways

should not be interpreted as uniformly emission-reducing. Mechanization and structural adjustment may increase emissions when they are based on energy-intensive inputs or rigid production patterns, while digital development and green technologies may improve resource-use efficiency and support low-carbon production. Therefore, the pathway results provide exploratory evidence that labor reallocation is accompanied by multiple transformation-related changes, although these associations should not be interpreted as causal mediation channels.

Third, the threshold results further show that the marginal association between non-agricultural employment and agricultural carbon emission intensity varies across levels of economic development and urbanization. This finding extends the stage-dependent interpretation of agricultural low-carbon transformation. Higher economic development and urbanization levels may improve infrastructure, capital availability, and technology diffusion. However, under current development conditions, these factors may also strengthen capital- and input-intensive production before green agricultural technologies and low-carbon service systems are fully mature. This helps explain why the emission-increasing effect of non-agricultural employment may become stronger after certain thresholds are crossed. Therefore, economic development and urbanization should be understood not only as drivers of green transformation, but also as boundary conditions that determine whether labor reallocation is more strongly associated with high-carbon substitution or low-carbon upgrading.

Fourth, the spatial econometric results indicate that the association between non-agricultural employment and agricultural carbon emission intensity extends beyond local regions through significant spatial spillover patterns. This finding is consistent with spatial economics and agricultural carbon-emission studies emphasizing spatial dependence, technology diffusion, and interregional production linkages. Agricultural production decisions, service outsourcing, labor mobility, and technological adoption are not confined within administrative boundaries. Therefore, changes in employment structure in one city may be associated with agricultural carbon emission intensity in neighboring cities through demonstration effects, service networks, factor flows, and regional market connections. The significant direct, indirect, and total effects identified in the Spatial Durbin Model suggest that ignoring spatial dependence may lead to an incomplete understanding of the carbon consequences of non-agricultural employment.

Overall, these findings contribute to the literature by showing that the relationship between non-agricultural employment and agricultural carbon emission intensity is not simply linear or homogeneous. Instead, it is nonlinear, stage-dependent, spatially connected, and conditioned by local development contexts. This highlights the need to design agricultural carbon-reduction policies according to regional development stages, production functions, and spatial linkages.

6. Conclusions

6.1. Main Research Conclusions

This study provides empirical evidence of a nonlinear and spatially interconnected association between non-agricultural employment and agricultural carbon emission intensity in China. Specifically, a significant inverted U-shaped relationship is identified, suggesting that the estimated relationship changes from emission-increasing to emission-reducing as labor reallocation deepens. The pathway analysis suggests that labor transfer is associated with changes in mechanization, production structure, and digital development, although these findings should be interpreted as exploratory evidence rather than definitive causal mechanisms. The threshold analysis further indicates that the magnitude of the estimated association varies across different stages of economic development and urbanization.

Furthermore, the Spatial Durbin Model reveals that the inverted U-shaped relationship extends beyond local regions through significant spatial spillover effects. Both the direct and indirect effects indicate that labor transfer influences agricultural carbon emission intensity across neighboring regions, highlighting the spatial interconnectedness of agricultural transformation.

Overall, the results underscore the importance of promoting labor mobility, technological upgrading, and regional coordination in advancing agricultural decarbonization and sustainable rural development.

6.2. Policy Implications

The findings of this study suggest that agricultural carbon-reduction policies should follow a logical sequence of “diagnosis–prescription–enablers,” rather than adopting a uniform policy package across all regions.

First, local governments should identify the development stage of each city in the nonlinear relationship between non-agricultural employment and agricultural carbon emission intensity. The estimated turning point of the non-agricultural employment ratio provides a useful reference for distinguishing cities that are still on the emission-increasing segment from those that have entered the emission-reducing segment. For cities below the turning point, policy attention should focus on reducing the risk of high-carbon substitution associated with labor outflow. For cities above the turning point, policies should further support the low-carbon transformation associated with scale operation, technological upgrading, and improved resource allocation.

Second, differentiated policy measures should be adopted according to regional development stages and resource endowments. In regions where non-agricultural employment remains positively associated with agricultural carbon emission intensity, governments should guide the substitution of labor with low-carbon technologies rather than conventional energy-intensive inputs. This includes promoting energy-saving agricultural machinery, reducing excessive fertilizer and pesticide use, expanding precision agriculture, and improving agricultural technology-extension services. In regions that have already entered the emission-reducing stage, policies should encourage land consolidation, green mechanization, digital agriculture, and agricultural producer services to accelerate the transition toward low-carbon and intensive production.

Third, policy design should pay particular attention to regions with strong emission-increasing effects, such as low-arable-land regions, major grain-producing regions, and non-urban-agglomeration cities. Low-arable-land regions should avoid small-scale, inefficient, and high-carbon machinery substitution by improving access to agricultural services and green technologies. Major grain-producing regions should balance food-security responsibilities with low-carbon production by improving the structure of subsidies and encouraging green machinery, precision fertilization, straw return, and conservation tillage. Non-urban-agglomeration cities should strengthen infrastructure, digital platforms, and agricultural service systems to reduce their dependence on traditional high-carbon input substitution.

Fourth, cross-regional coordination should be strengthened to make full use of spatial spillover effects. Since non-agricultural employment is associated with agricultural carbon emission intensity not only locally but also in neighboring regions, local governments should promote interregional cooperation in low-carbon technology diffusion, agricultural service outsourcing, machinery sharing, and carbon-reduction governance. Regional coordination mechanisms can help spread green production practices from more developed regions to surrounding areas and reduce the risk of carbon leakage or duplicated high-carbon investment.

Finally, digital infrastructure and green agricultural service systems should be treated as key enablers of agricultural low-carbon transformation. Investment in rural digital networks, smart agricultural equipment, agricultural data platforms, and producer-service organizations can improve resource allocation efficiency and accelerate the shift from labor-saving but energy-intensive substitution to energy-saving technological upgrading. These enabling conditions are particularly important for regions that have not yet crossed the emission-reduction turning point.

6.3. Limitations

1. The first challenge lies in measuring non-agricultural employment. Due to inconsistencies in existing statistical definitions of labor mobility, it is difficult to accurately capture the degree of labor transfer out of agriculture. To address this issue, this study utilizes long-term, consistently available data at the prefecture-level city scale and measures non-agricultural employment as the ratio of employment in the secondary and tertiary sectors to total employment, thereby ensuring the stability and comparability of the indicator.
2. The second challenge concerns the accounting of agricultural carbon emissions. Given the diversity of emission sources and the fragmented nature of data, differences in accounting approaches may lead to estimation bias. To mitigate this problem, this study follows the IPCC guidelines for carbon accounting and integrates mainstream approaches in the literature. Specifically, an input–output-based method is adopted to systematically calculate emissions from multiple sources, including fertilizers, pesticides, agricultural film, and machinery power. Sensitivity analysis is further conducted to verify the robustness of the results.
3. The third challenge involves identifying the underlying mechanisms and addressing spatial effects. The relationship between non-agricultural employment and carbon emissions may involve multiple pathways and spatial spillovers, making empirical identification more complex. To tackle this issue, this study incorporates three key theoretical perspectives—industrial structure, factor allocation, and industrial agglomeration—into the analytical framework. Empirically, both pathway analysis models and a Spatial Durbin Model are employed to jointly capture transmission pathways and regional interactions, ensuring logical rigor and empirical reliability in mechanism identification. It should also be noted that the carbon-emission inventory mainly captures input-related emission sources and does not directly include methane emissions from rice cultivation, enteric fermentation, or livestock waste management due to data limitations. Although additional sensitivity analyses indicate that the main findings remain qualitatively unchanged, the reported estimates should be interpreted as partial measures of agricultural greenhouse-gas emissions.
4. The fourth challenge concerns causal identification. Although the fixed-effects and instrumental-variable specifications provide supplementary evidence, potential endogeneity cannot be fully eliminated. In particular, lagged non-agricultural employment may still be correlated with unobserved development conditions. Future research could use stronger identification strategies, such as historical migration networks, policy shocks, or exogenous labor-demand shocks, to establish causal effects more convincingly.
5. The fifth challenge concerns the interpretation of pathway analysis. The pathway analysis focuses on the associations between non-agricultural employment and selected transformation-related variables. Although these results provide useful insights into potential pathways, they do not establish formal causal transmission mechanisms. Future studies may employ more sophisticated identification strategies

and richer micro-level data to further examine the channels through which labor transfer affects agricultural carbon emissions.

6. Another limitation is that this study focuses on agricultural carbon emissions rather than the net agricultural carbon balance. Due to data limitations, carbon sequestration from crops, soils, conservation tillage, straw return, and other agricultural ecosystem processes is not incorporated into the accounting framework. Therefore, the results reflect changes in agricultural carbon emission intensity, not net agricultural carbon emissions. Future research could integrate both agricultural carbon sources and carbon sinks to evaluate the net carbon-neutrality performance of agricultural systems more comprehensively.

In the future, with the gradual updating of statistical data and the continuous advancement of spatial econometric methods, further research can provide a more detailed examination of the relationship between non-agricultural employment and agricultural carbon emission intensity. In particular, more in-depth analysis can be conducted on the dynamic evolution, transmission mechanisms, and spatial spillover effects associated with labor reallocation. Moreover, future studies may explore more thoroughly the heterogeneous impacts and development dynamics driven by the positive externalities of non-agricultural employment across different regions. Such efforts will help to further enrich and refine the findings of this study.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18136883/s1>. Table S1: Variable definitions, calculation methods, and data sources; Table S2: Agricultural carbon emission sources and coefficients. References [76,82] are cited in the Supplementary Materials.

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