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# Non-Grain Conversion of Cropping Structure and Agricultural Carbon Emissions: Evidence from China's County-Level Panel Data

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**ABSTRACT:** China's non-grain conversion of cropping structure provides an empirical context for understanding how intra-arable crop composition adjustments affect county-level agricultural carbon emissions. However, local governments must simultaneously safeguard food security, farmer incomes, and low-carbon transitions, while farmers adjust crop choices in response to relative returns, production constraints, and policy boundaries. Using an unbalanced panel dataset of Chinese counties from 2000 to 2020, this paper constructs a non-grain conversion rate indicator and employs a two-way fixed-effects model at the county and year levels to examine the relationship between non-grain conversion and agricultural sector carbon emissions. The findings indicate that, after controlling for county fixed effects and annual common shocks, the non-grain conversion rate is significantly and positively correlated with agricultural carbon emissions. This conclusion remains generally robust after winsorization, alternative measures, and adjusted clustering levels. Mechanism results reveal that non-grain conversion creates emission pressures by increasing the proportion of cash crop cultivation, intensifying high-input production practices, and weakening the efficiency advantages of scale and mechanization. Heterogeneity results show that this relationship is stronger in major grain-producing areas, southern paddy field regions, the Yangtze River Economic Belt, counties with higher development levels, and counties with larger populations, while exhibiting different directions in some non-major producing areas, dryland regions, and counties with lower development levels. This paper integrates land use transition, crop composition choice, and agricultural carbon emissions into a unified analytical framework, demonstrating that non-grain conversion governance should not be understood as merely area-based regulation, but rather as institutional coordination embedded among food security, agricultural returns, and low-carbon transitions.

**Keywords:** Non-grain conversion of cropping structure, Agricultural carbon emissions, Land use transition, Two-way fixed effects, Low-carbon agriculture.

## 1. INTRODUCTION

The challenge of agricultural emission reduction lies not only in reducing individual input intensities, but also in explaining why production structures evolve along different emission pathways. Food systems research has demonstrated that agriculture, land use, processing, and transportation collectively contribute a substantial share of global greenhouse gas emissions (Crippa *et al*., 2021; Xu *et al*., 2021); nitrogen cycling, livestock, and paddy field processes further make agriculture a significant source of methane and nitrous oxide (Tian *et al*., 2020; Poore & Nemecek, 2018; Springmann *et al*., 2018). Existing life cycle assessments also indicate that different agricultural product categories exhibit differentiated emission intensities, and that input structures and production organization methods alter the environmental performance per unit of land and per unit of output (Clune *et al*., 2017; Pelletier *et al*., 2011; Tubiello *et al*., 2015; Leip *et al*., 2021). This implies that agricultural carbon

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emissions are not the result of any single production link, but rather a comprehensive outcome shaped by land allocation, crop structure, input use, and farm management organization. International gridded emission accounting emphasizes fine-scale sectoral identification (Crippa *et al*., 2018; Janssens-Maenhout *et al*., 2019), which raises a question: when the crop composition within arable land shifts from grain crops to cash crops or other non-grain uses, how do county-level agricultural carbon emissions change? This question matters because, in practice, agricultural low-carbon transitions typically do not occur within static agricultural structures, but rather in dynamic processes where crop choices, market demands, and local policies are constantly adjusting. Furthermore, green transitions in developing countries are continuously coordinated among market incentives, institutional constraints, and local governance, rather than being accomplished through technology alone. If crop structure adjustments are neglected, agricultural emission reduction research may mistakenly attribute emission changes to technical efficiency changes while overlooking the contribution of production structure itself.

China's non-grain conversion of cropping structure provides a research context with institutional significance for addressing this question. Food system transitions in developing countries are typically driven jointly by market demand, supply chain expansion, agricultural technology, and land management institutions (Reardon *et al*., 2019). In China, strict farmland protection and food security responsibility systems require local governments to safeguard farmers' land rights and grain production capacity, while farmers and local economies face continuous incentives from returns, labor costs, consumption structure upgrading, and agricultural modernization investments. Non-grain conversion of cropping structure occurs precisely between these two forces; it is not equivalent to simple construction land occupation, nor is it merely farmers' free choice of crops. Rather, it is the result of the joint action of food security institutions, land management institutions, agricultural comparative returns, and market-oriented agricultural transitions. Existing international studies have shown that non-grain production on China's cultivated land exhibits significant spatio-temporal variation and is influenced jointly by land transfer, farmland multifunctionality, agricultural suitability, and grain production potential (Feng *et al*., 2022; Su *et al*., 2024; Chen *et al*., 2023; Zhu *et al*., 2022; Pu, 2025). Therefore, whether non-grain conversion increases or decreases agricultural carbon emissions depends critically on which specific crops, inputs, and management practices it changes. If non-grain conversion manifests primarily as expansion of protected vegetables, orchards, floriculture, and high-frequency multiple cropping, its emission consequences may differ from drought-resistant cash crops or low-input substitutes. Moreover, if non-grain conversion occurs in major grain-producing areas, its institutional implications differ from conventional crop adjustments in non-major producing areas. Many developing economies face trade-offs among food security, farmer incomes, and environmental constraints, and China's county-level governance system offers certain empirical evidence.

The existing literature provides three foundations for this paper, but also leaves clear gaps. First, food systems and life cycle assessment literature has demonstrated that different agricultural products have different emission intensities and that input use and land use change are important sources of agricultural emissions (Clune *et al*., 2017; Pelletier *et al*., 2011; Tubiello *et al*., 2015; Leip *et al*., 2021), but these studies rarely explain the dynamic effects of intra-county crop structure adjustments. Second, land use transition research focuses on land carbon sources, carbon sinks, and regional carbon balances, showing that land structural changes alter carbon emission patterns (Luo *et al*., 2022; Chuai *et al*., 2015), but pays insufficient attention to intra-arable "grain–non-grain" conversion. Third, research on China's non-grain conversion has described spatial patterns and driving factors (Feng *et al*., 2022; Su *et al*., 2024; Chen *et al*., 2023; Zhu *et al*., 2022; Pu, 2025), but has rarely positioned non-grain conversion within a unified framework of agricultural carbon emissions, production inputs, and mechanization efficiency. In other words, existing research has paid adequate attention to land transition and agricultural carbon emissions issues, but has not yet fully answered how this specific form of land use transition, "non-grain conversion", changes agricultural emissions. Existing studies typically discuss non-grain conversion as a food security risk, rather than treating it as a structural variable in agricultural green transitions, which causes policy discussions to remain at whether to regulate non-grain conversion. Therefore, connecting the two is important: non-grain conversion is a concrete manifestation of land use transition, agricultural carbon emissions are the environmental outcome of this transition, and inputs and mechanization are the behavioral mechanisms connecting the two, this connection represents a relatively weak link in current literature.

Accordingly, this paper addresses the following three questions: First, after controlling for county fixed characteristics and annual common shocks, is the non-grain conversion rate systematically related to agricultural carbon emissions? Second, is this relationship realized through changes in crop composition, input intensity, and mechanization efficiency? Third, under different grain functional zones, cultivated land types, development stages, and population scales, do the emission consequences of non-grain conversion differ? The potential marginal contributions of this paper lie in: extending non-grain conversion from a food security issue to an agricultural low-carbon transition issue, using county panel data to identify the relationship between intra-county cropping structure changes and agricultural carbon emissions, and integrating average effects, mechanism effects, and regional heterogeneity into a unified explanatory framework. This paper does not directly interpret static differences between counties as non-grain conversion effects, but rather utilizes within-county variation over time for identification, to avoid mistakenly attributing natural differences between mountainous counties, plain counties, suburban counties, and traditional grain counties to the effects of non-grain conversion.

## 2. THEORETICAL FRAMEWORK

The institutional background of China's non-grain conversion problem features three constraints. The first constraint comes from food security and farmland protection, where policies such as the farmland red line, permanent basic farmland protection, major grain-producing area responsibilities, and local food security assessments collectively constitute the institutional baseline for grain production capacity. The second constraint comes from agricultural green transitions, where requirements for low-carbon agriculture, chemical fertilizer and pesticide reduction, water-saving irrigation, and agricultural mechanization upgrading demand that localities reduce resource and environmental pressures while increasing agricultural output. The third constraint comes from the return incentives of farmers and local governments, where cash crops, protected agriculture, and specialty agriculture often offer higher market returns, and local governments may also treat them as important directions for agricultural value addition and rural industrial revitalization. Non-grain conversion is precisely the cropping structure adjustment formed among these three constraints (Feng *et al*., 2022; Su *et al*., 2024; Chen *et al*., 2023; Zhu *et al*., 2022; Pu, 2025). This institutional structure determines that non-grain conversion is the result of joint responses by local governments, farmers, and markets. Local governments balance food security responsibilities and agricultural income growth targets, while farmers make choices among returns, labor inputs, and risk expectations. In this institutional context, local governments are not merely regulators but may also be promoters of agricultural structural adjustments. To increase agricultural value added, develop specialty industries, and raise farmer incomes, localities may support the development of cash crops, protected agriculture, and leisure agriculture, but when these transitions occupy high-quality arable land or increase high-carbon inputs, tensions arise with food security and low-carbon objectives. Non-grain conversion is not isolated farmer behavior, but rather a structural phenomenon within a multi-objective governance system. This institutional background determines that the environmental effects of non-grain conversion are not a priori determinate. On the one hand, if non-grain conversion manifests as expansion of high-value-added cash crops, protected agriculture, or high-frequency multiple cropping, it may increase chemical fertilizer, pesticide, plastic film, irrigation, and energy inputs, thereby increasing agricultural carbon emissions. On the other hand, if non-grain conversion occurs in dryland areas, with low-input crops, or in areas previously under low-efficiency grain production, it may also reduce certain input intensities.

Theoretically, non-grain conversion affects agricultural carbon emissions through at least three mechanisms. The first is the input intensity mechanism. Cash crops and protected agriculture typically require higher-intensity inputs of chemical fertilizers, pesticides, irrigation, plastic film, and energy. Excessive pesticide use reduces agricultural green production efficiency and brings indirect energy consumption (Zhang *et al*., 2015), while nitrogen fertilizer use also generates greenhouse gas pressures through production processes and soil nitrous oxide emissions (Snyder *et al*., 2009). The second is the crop composition mechanism. Different crop categories have different life-cycle emission intensities, multiple cropping systems, and management methods (Clune *et al*., 2017; Fan *et al*., 2022; Sui & Lv, 2021). Grain crops typically rely more on standardized field management, while some cash crops require more intensive pest and disease control, temperature control, irrigation, and harvesting management. Non-grain conversion changes farmers' comprehensive choices regarding input intensity, multiple cropping systems, and market returns; an increase in the proportion of cash crops may intensify high-input production practices. The third is the mechanization and scale efficiency mechanism. Grain crop production is more amenable to standardized, large-scale, and mechanized operations, while some cash crops require higher-frequency, more refined management. Agricultural mechanization does not necessarily increase emissions; under conditions of scale management and technical efficiency improvement, mechanization may reduce emissions per unit of output (Guan *et al*., 2023; Yang *et al*., 2022). If non-grain conversion weakens the scale management and mechanization efficiency of the grain production system, it may indirectly increase emission pressures by reducing energy and machinery service use efficiency. If non-grain conversion leads to more dispersed crop types and more complex plot management, even if machinery inputs do not increase, energy efficiency per unit of output may decline. Increased emissions may not come from absolute increases in total machinery power, but rather from losses in mechanization efficiency and scale economies.

The above three mechanisms do not operate in isolation but rather interact and work jointly. An increase in the proportion of cash crops is often accompanied by higher input intensity, while crop diversification may weaken mechanization efficiency. Therefore, the effect of non-grain conversion on carbon emissions is the combined result of crop composition adjustment, input structure change, and scale efficiency loss.

Based on the above analysis, this paper proposes the following hypotheses:

H1: The non-grain conversion rate of cropping structure promotes county-level agricultural carbon emissions.

H2: Non-grain conversion of cropping structure affects agricultural carbon emissions by changing agricultural mechanization and scale management conditions.

H3: Non-grain conversion of cropping structure affects agricultural carbon emissions by increasing the proportion of cash crops and high-input production practices.

## 3. SPATIAL PATTERN CHARACTERISTICS AND VISUAL ANALYSIS

Figure **1** presents the spatial distribution of agricultural carbon emissions at the county level in China. Overall, high-value areas of agricultural carbon emissions are not uniformly distributed, but are jointly related to population, agricultural production intensity, crop structure, and regional resource endowments. Parts of eastern and central China with intensive agriculture, certain counties

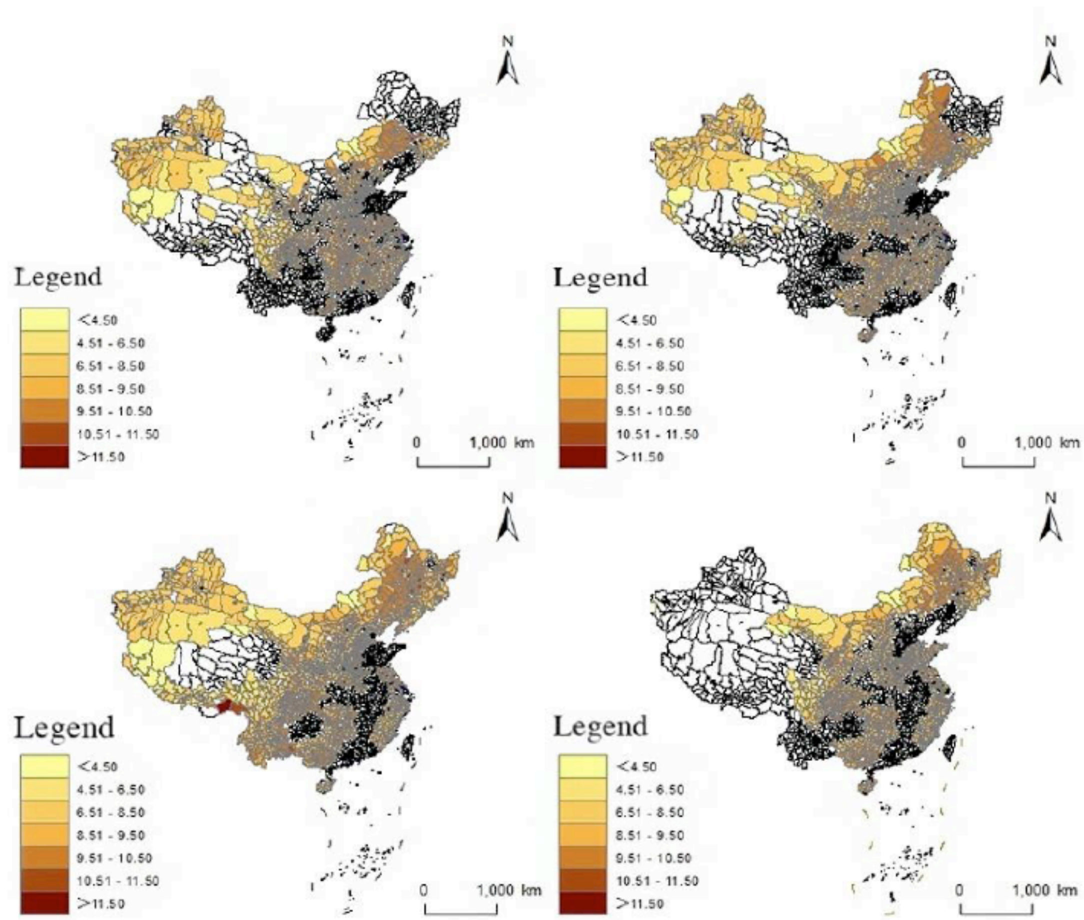


**Figure 1:** Spatial Distribution of County-Level Agricultural Carbon Emissions in China.

in the Yangtze River basin, and areas with higher population and agricultural input densities exhibit higher emission levels, while western regions and areas with stronger ecological constraints show relatively lower values. Agricultural carbon emissions exhibit clear regional agglomeration characteristics; therefore, subsequent models need to control for time-invariant geographical endowments at the county level and further examine heterogeneity across grain functional zones, cultivated land types, and regional development levels. More importantly, the spatial distribution reminds us that the carbon emission effects of non-grain conversion cannot be understood apart from regional production institutions. The same non-grain conversion may imply expansion of high-input production in counties with abundant water and heat conditions, developed protected agriculture, and high population density, while in dry farming areas or ecologically fragile areas, it may imply different crop substitutions and resource utilization methods. Moreover, county-level spatial differences are far more complex than provincial averages; if provincial-level data were used, many high-emission and low-emission counties would be averaged within the same province, making it difficult to identify true spatial agglomeration. This paper's insistence on using county panel data is precisely to preserve this fine-scale variation and to provide an empirical basis for subsequent groupings by major grain-producing areas, cultivated land types, and population scales.

## 4. RESEARCH DESIGN

### 4.1. Variable Selection and Measurement

**(1) Dependent variable: Agricultural sector carbon emissions**

The dependent variable is county-level agricultural sector carbon dioxide emissions. This paper obtains the agricultural sector emission indicator from the RStata Data Center's China provincial, municipal, and county-level sectoral carbon emission data and applies a natural logarithm transformation. Since this indicator primarily reflects agricultural sector $CO_2$ emissions, this paper uses "agricultural carbon emissions" as a shorthand in the text. The construction logic of the relevant emission data is consistent with the sectoral and spatial accounting approaches emphasized by international emission inventories such as EDGAR (Crippa *et al*., 2018; Janssens-Maenhout *et al*., 2019).

**(2) Core explanatory variable: Non-grain conversion rate of cropping structure**

The core explanatory variable is the non-grain conversion rate of cropping structure, measured as the proportion of non-grain crop sown area in total crop sown area. A higher value of this indicator indicates that the county's arable land cropping structure is more oriented toward cash crops or other non-grain uses. This indicator differs from "non-agriculturalization" indicators, where non-agriculturalization typically refers to the conversion of cultivated land to construction land or other non-agricultural uses. The non-grain conversion in this paper still occurs within the agricultural production system, with its core being the structural adjustment between grain crops and non-grain crops.

**(3) Control variables**

To reduce omitted variable bias, this paper controls for the following variables: total population at year-end (ln); industrial structure, measured as the ratio of primary industry value added to regional gross domestic product; economic development level, measured as per capita regional gross domestic product (ln); fiscal decentralization, measured as the ratio of county-level fiscal budgetary revenue to budgetary expenditure; and

**Table 1: Definitions of Main Variables**

| Variable Name | Symbol | Variable Meaning and Definition |
|---|---|---|
| Agricultural sector carbon emissions | *lnCO2* | Agricultural Sector Carbon Emissions (ln) |
| Non-grain conversion rate of cropping structure | *ngr* | (Total Crop Sown Area – Grain Crop Sown Area) / Total Crop Sown Area |
| Total population | *lnpop* | Year-end Total Population (ln) |
| Industrial structure | *TS* | Value Added of Primary Industry / GDP |
| Fiscal decentralization | *fd* | County-level Budgetary Revenue / County-level Budgetary Total Expenditure |
| Economic development level | *lnpgdp* | Per Capita GDP (ln) |
| Fiscal support for agriculture | *gov* | Fiscal Budget Expenditure / GDP |

fiscal support for agriculture, measured as the ratio of fiscal budgetary expenditure to regional gross domestic product.

The original data in this paper cover China's county-level sample from 2000 to 2022, sourced from the RStata Data Center, the China County Statistical Yearbook, and provincial statistical yearbooks. Due to county-level administrative adjustments, changes in statistical scope, and missing values for some variables, the main regression sample after merging core and control variables is an unbalanced panel of 2000-2020, 1,343 county units, and 14,162 county-year observations. For identifiable short-term missing values, this paper uses linear interpolation for supplementation.

Table **2** reports the descriptive statistics for the main variables entering the main regression. The mean non-grain conversion rate is approximately 0.35, indicating that non-grain crop sown area already accounts for a considerable proportion in the sample counties. The mean of $lnCO_2$ is 8.77, with a large standard deviation, indicating significant spatial and temporal differences in county-level agricultural emissions. The extreme values of control variables also suggest large differences in county-level economic development and fiscal structure, which further indicates the necessity of using fixed-effects models and heterogeneity analysis. Because county-level administrative adjustments, county-to-district conversions, missing statistical reports, and scope changes result in incomplete consistency of sample years across counties, this paper does not forcibly construct a balanced panel, avoiding sample selection bias that would arise from deleting large numbers of counties.

Figure **2** shows the annual trends of the mean non-grain conversion rate and mean agricultural carbon emissions. Because the two variables have different units and ranges, the figure is intended primarily to present long-term trajectories and phased fluctuations. Overall, the non-grain conversion rate exhibits a fluctuating upward trend during the sample period, while agricultural carbon emissions remain at relatively high levels with phased adjustments. The figure indicates that time trends alone cannot determine whether non-grain conversion increases emissions, because concurrent influences may include agricultural technological progress, energy-saving policies, changes in statistical scope, and macroeconomic fluctuations. Therefore, the subsequent model absorbs national-level common shocks through year fixed effects and excludes time-invariant county-level endowment differences through county fixed effects.

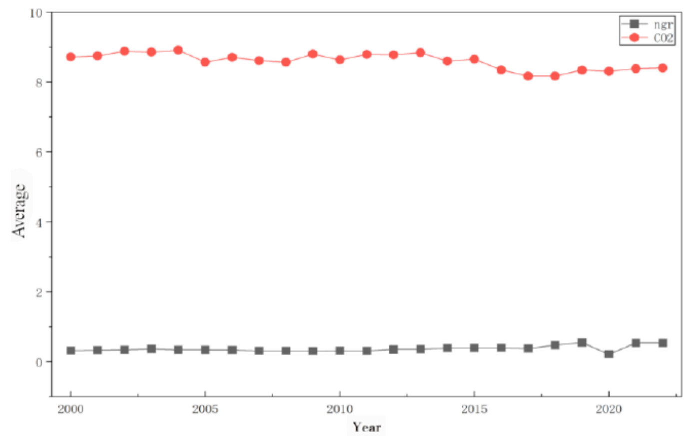


**Figure 2:** Temporal Evolution of Mean Values of Core Variables.

### 4.2. Econometric Model

To examine the relationship between non-grain conversion of cropping structure and agricultural carbon emissions, this paper constructs the following two-way fixed-effects model:

$$lnCO2_{it}=\alpha+\beta ngr_{it}+\gamma control_{it}+\mu_i+\delta_t+\varepsilon_{it} \quad (1)$$

where $lnCO2_{it}$ represents the logarithm of agricultural sector carbon emissions for county $i$ in year $t$; $ngr_{it}$

**Table 2: Descriptive Statistics of Variables**

| Variables | N | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| *CO2* | 14162 | 9755.08 | 7658.01 | 0.09 | 126908.12 |
| *lnCO2* | 14162 | 8.77 | 1.20 | -2.39 | 11.75 |
| *ngr* | 14162 | 0.35 | 0.17 | 0.00 | 1.00 |
| *lnpop* | 14162 | 3.55 | 0.81 | 0.00 | 5.35 |
| *TS* | 14162 | 0.24 | 0.14 | 0.00 | 0.83 |
| *lnpgdp* | 14162 | 9.47 | 1.06 | 6.44 | 13.04 |
| *fd* | 14162 | 0.40 | 0.25 | 0.00 | 4.71 |
| *gov* | 14162 | 0.16 | 0.14 | 0.01 | 2.40 |

represents the non-grain conversion rate of cropping structure for county $i$ in year $t$; $control_{it}$ represents the vector of control variables; the county fixed effect $\mu_i$ controls for time-invariant factors such as topography, climate, cultivated land endowments, and agricultural traditions; the year fixed effect $\delta_t$ controls for national common shocks; and model estimation follows general practices in panel data fixed-effects analysis (Wooldridge, 2010).

## 5. EMPIRICAL RESULTS

### 5.1. Baseline Regression

Table **3** reports the baseline regression results. Columns (1) and (2) present OLS estimates without fixed effects, where the coefficient on the non-grain conversion rate is significantly negative. This result does not mean that non-grain conversion reduces agricultural carbon emissions, but rather likely reflects confounding from county-level endowment differences and omitted variables. For example, certain mountainous and hilly counties have lower grain cultivation proportions and higher non-grain conversion rates, but may also have smaller agricultural production scales and lower carbon emission bases; without controlling for such inherent county differences, OLS estimates are prone to directional bias. Column (3), which controls only for year fixed effects, still yields a negative coefficient, indicating that national common shocks are not the sole source of OLS bias. The truly critical factor is long-standing geographical, production tradition, and agricultural scale differences between counties. This is also the importance of county fixed effects in this paper. This directional reversal is not uncommon in land use and agricultural research, because cross-sectional differences often confound natural endowments, agricultural scale, and historical paths. Plain grain counties may have high emissions but low non-grain conversion, while hilly cash crop counties may have high non-grain conversion but low emission bases. Without distinguishing between cross-sectional differences and temporal variation, conclusions opposite to the mechanisms may be drawn. Column (4), which controls for county fixed effects, shows

**Table 3: Baseline Regression Results**

| lnCO2 | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | OLS | OLS+control | FE | FE | FE |
| ngr | -1.2082*** | -1.0194*** | -1.0651*** | 0.2147*** | 0.0716*** |
| | (0.0856) | (0.0743) | (0.0769) | (0.0222) | (0.0083) |
| lnpop | | 0.9351*** | 1.0018*** | 0.0855*** | -0.0007 |
| | | (0.0152) | (0.0178) | (0.0222) | (0.0083) |
| TS | | 2.3724*** | 2.3730*** | -0.0445 | -0.0194* |
| | | (0.1099) | (0.1108) | (0.0323) | (0.0116) |
| lnpgdp | | 1.2588*** | 1.5946*** | -0.0891*** | 0.1226*** |
| | | (0.1270) | (0.1314) | (0.0293) | (0.0105) |
| lnpgdp2 | | -0.0639*** | -0.0725*** | -0.0011 | -0.0054*** |
| | | (0.0068) | (0.0070) | (0.0015) | (0.0005) |
| fd | | -0.6600*** | -0.9374*** | 0.0936*** | -0.0177*** |
| | | (0.0526) | (0.0748) | (0.0110) | (0.0038) |
| gov | | -0.4546*** | -0.0403 | -0.0124 | 0.1422*** |
| | | (0.0981) | (0.1285) | (0.0229) | (0.0154) |
| County Effect | NO | NO | NO | YES | YES |
| Time Effect | NO | NO | YES | NO | YES |
| _cons | 9.1897*** | -0.5418 | -3.1137*** | 9.3067*** | 8.0633*** |
| | (0.0293) | (0.6013) | (0.6365) | (0.1662) | (0.0637) |
| N | 14162 | 14162 | 14162 | 14092 | 14092 |
| adj. R2 | 0.030 | 0.541 | 0.556 | 0.985 | 0.998 |

**Note:** Robust standard errors in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The same applies below.

that the coefficient on the non-grain conversion rate turns from negative to positive and becomes significant. Column (5), which simultaneously controls for county and year fixed effects, yields a coefficient of 0.0716, significant at the 1% level. This indicates that, when comparing within the same county and netting out annual common shocks, higher non-grain conversion rates are significantly associated with increased agricultural carbon emissions, providing preliminary support for H1.

### 5.2. Endogeneity Treatment and Robustness Tests

Table **4** reports endogeneity treatment and robustness tests. Column (1) uses the lagged one-period non-grain conversion rate as an instrumental variable for 2SLS estimation. In terms of relevance, current-period non-grain behavior is a continuation of previous planting structure transitions, and the lagged one-period non-grain conversion rate is significantly positively correlated with the current-period rate, satisfying the relevance requirement of instrumental variables. In terms of exogeneity, the lagged one-period non-grain conversion decision occurs before current-period carbon emissions, is not directly affected by reverse causation from current-period agricultural carbon emissions, and does not affect current-period carbon emission intensity through unobserved factors, satisfying the exogeneity requirement of instrumental variables. The instrumental variable regression results show that the coefficient on the core explanatory variable is positive and significant at the 1% level, indicating that after effectively mitigating endogeneity concerns, non-grain conversion of cropping structure still significantly increases agricultural carbon

**Table 4: Endogeneity Treatment and Robustness Tests**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | **2SLS** | **Winsorization** | **Replace ngr** | **City cluster** | **15 years** | **18 years** | **Province fixed** |
| ngr | 0.1664*** | | | 0.0716*** | 0.0641*** | 0.0846*** | 0.0716*** |
| | (0.0158) | | | (0.0204) | (0.0085) | (0.0093) | (0.0083) |
| ngr_w | | 0.0871*** | | | | | |
| | | (0.0089) | | | | | |
| ngr2 | | | 0.0716*** | | | | |
| | | | (0.0083) | | | | |
| lnpop | 0.0286*** | 0.0084 | -0.0007 | -0.0007 | 0.0034 | -0.0048 | -0.0007 |
| | (0.0093) | (0.0089) | (0.0088) | (0.0198) | (0.0086) | (0.0112) | (0.0083) |
| TS | -0.0249* | -0.0287** | -0.0194* | -0.0194 | -0.0392*** | -0.0249* | -0.0194* |
| | (0.0139) | (0.0126) | (0.0116) | (0.0269) | (0.0122) | (0.0131) | (0.0116) |
| lnpgdp | 0.1314*** | 0.1248*** | 0.1226*** | 0.1226*** | 0.1258*** | 0.1500*** | 0.1226*** |
| | (0.0121) | (0.0111) | (0.0105) | (0.0266) | (0.0106) | (0.0126) | (0.0105) |
| lnpgdp2 | -0.0055*** | -0.0054*** | -0.0054*** | -0.0054*** | -0.0056*** | -0.0069*** | -0.0054*** |
| | (0.0006) | (0.0006) | (0.0005) | (0.0014) | (0.0005) | (0.0006) | (0.0005) |
| fd | -0.0212*** | -0.0220*** | -0.0177*** | -0.0177** | -0.0200*** | -0.0110** | -0.0177*** |
| | (0.0043) | (0.0041) | (0.0038) | (0.0073) | (0.0040) | (0.0047) | (0.0038) |
| gov | 0.1626*** | 0.1491*** | 0.1422*** | 0.1422*** | 0.1493*** | 0.1317*** | 0.1422*** |
| | (0.0199) | (0.0157) | (0.0154) | (0.0350) | (0.0165) | (0.0180) | (0.0154) |
| County Effect | YES | YES | YES | YES | YES | YES | YES |
| Time Effect | YES | YES | YES | YES | YES | YES | YES |
| _cons | | 8.0236*** | 8.0633*** | 8.0633*** | 8.0716*** | 8.0258*** | 8.0633*** |
| | | (0.0684) | (0.0637) | (0.1468) | (0.0643) | (0.0800) | (0.0637) |
| N | 12500 | 14092 | 14092 | 14092 | 12943 | 11817 | 14092 |
| adj. R2 | -0.052 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 | 0.998 |

emissions. Column (2) applies winsorization treatment to core variables; Column (3) uses (1 − Crop sown area / Grain crop sown area) as an alternative measure of the non-grain conversion rate; and Column (4) clusters standard errors at the city level. All regression results remain positive and significant, indicating that the conclusion is not driven by measurement criteria or extreme values, and that the positive relationship between non-grain conversion and agricultural carbon emissions has good robustness. Since the sample used for the baseline regressions is an unbalanced panel covering 2000-2020, some county-level units have missing data due to administrative boundary adjustments or statistical interruptions. To mitigate potential sample selection bias arising from the unbalanced panel, we construct more balanced panel subsamples by retaining county-level units observed for at least 15 and 18 years, respectively. There are two reasons for this choice: first, these observation periods exceed the median sample duration, ensuring that the retained counties belong to the group that persisted over the medium to long term; second, these thresholds avoid severe damage to sample representativeness caused by overly strict balancing requirements. Columns (5) - (6) present the estimation results based on this subsample; it can be observed that the coefficients of the core explanatory variables are highly consistent with the baseline results, indicating that the unbalanced panel data did not affect the research conclusions.In addition, time-varying provincial factors may be correlated with both non-grain conversion and agricultural emissions, potentially biasing two-way fixed-effects estimates. Column (7) therefore simultaneously includes province-by-year fixed effects, absorbing all province-level time-varying shocks. The coefficient on non-grain conversion remains significantly positive, indicating that the baseline result is not driven by unobserved provincial regional dynamics.

Figure **3** further presents the partial regression relationship after removing control variables and fixed effects. The residual fitted line exhibits a positive slope, indicating that after controlling for observable variables, county fixed effects, and year fixed effects, a positive association still exists between the non-grain conversion rate and agricultural carbon emissions. Because partial regression plots are sensitive to extreme values, this paper still relies on the model estimates in Tables **3** and **4** as the primary basis for judgment. The role of this figure is primarily to visually present the “purified” variable relationship: the horizontal axis reflects non-grain conversion changes after removing county fixed characteristics, year shocks, and control variables, while the vertical axis reflects agricultural carbon emission changes after the same treatment. The upward-sloping fitted line indicates that the positive relationship between non-grain conversion and emissions is not simply caused by cross-sectional differences but persists after controlling for them.

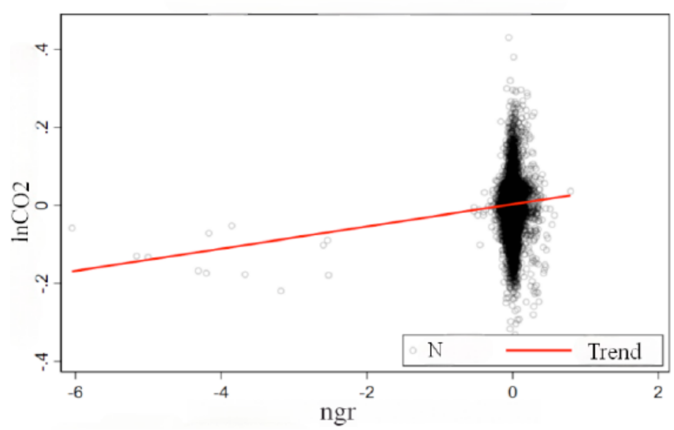


**Figure 3:** Partial Regression Fit Plot of Non-Grain Conversion Rate and Agricultural Carbon Emissions.

### 5.3. Spatial Spillover Effects

Agricultural production activities at the county level exhibit distinct spatial correlations; neighboring counties typically share similar resource endowments and regional agricultural product markets, and farming techniques, production experience, agricultural machinery services, and methods of agricultural input may also spread across county boundaries. Therefore, agricultural carbon emissions in a given county may be influenced not only by the shift away from grain crops in that county’s cropping structure but also by adjustments in the cropping structures of neighboring counties. To test this spatial relationship, this study incorporates a spatial lag term for the non-grain crop ratio in neighboring counties into the baseline model. Since this study focuses on the relationship between the shift away from grain crops in neighboring counties and carbon emissions in the target county, the Spatial Lag-Extended (SLX) model is employed. The specific specifications are as follows:

$$lnCO_{2it} = \alpha + \beta ngr_{it} + \theta W^{(K)} ngr_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In this model, $W^{(K)}ngr_{it}$ represents the spatial lag term for the non-grain cultivation rate in adjacent counties, calculated using a K-nearest-neighbor spatial weighting matrix, and is used to measure the degree of non-grain cultivation in the surrounding spatial environment of the county under study. The coefficient $\theta$ is a key spatial parameter; if $\theta$ is significantly positive, it indicates that an increase in the average non-grain cultivation rate in adjacent counties is associated with an increase in agricultural carbon emissions in the county under study.

Furthermore, since the dependent variable is expressed as a natural logarithm and the non-grain cultivation rate ranges from 0 to 1, the exact percentage change in this county's agricultural carbon emissions corresponding to a 10-percentage-point increase in the average non-grain cultivation rate of neighboring counties is:

$$[e^{0.1\theta}-1]\times 100\% \tag{3}$$

For each county, sort the distances between it and all other counties in ascending order, and select the 3, 5, and 8 closest counties, respectively. The unstandardized K-nearest-neighbor spatial weight matrix is defined as:

$$q_{ij}^{(K)}=\begin{cases}1, & j\in N_i^{(K)}, i\neq j\\ 0, & j\notin N_i^{(K)} \text{ or } i=j\end{cases} \tag{4}$$

$N_i^{(K)}$ denotes the set consisting of the $K$ counties geographically closest to county $i$. This spatial weight matrix may be directional; County $j$ may be among the five nearest neighbors of County $i$, but County $i$ may not necessarily be among the five nearest neighbors of County $j$. Therefore, this study standardizes the rows of the spatial weight matrix so that the spatial lag term can be directly interpreted as the average non-grain cultivation rate of adjacent counties.

When valid observations are available for all $K$ neighboring counties, $w_{ij}^{(K)} = 1/K$, and the sum of the weights in each row equals 1. In this case, the spatial lag term is:

$$W^{(K)}ngr_{it}=\frac{1}{K}\sum_{j\in N_i^{(K)}} ngr_{jt} \tag{5}$$

Therefore, when there are no missing annual observations for adjacent counties, the spatial lag term is defined as the average non-grain cultivation rate of the $K$ counties geographically closest to the current county in year $t$.

Furthermore, since the data in this study are unbalanced panel data, in a given year, one or more of the $K$ pre-determined adjacent counties may lack non-grain cultivation rate observations. Therefore, this study calculates the spatial lag term using only those adjacent counties with valid non-grain cultivation rate observations for the same year, and re-standardizes the weights within the set of adjacent counties available for that year:

**Table 5: Spatial Spillover Effects of Non-Grain Conversion**

| lnCO□ | (1) | (2) | (3) |
|---|---|---|---|
| | 3 nearest counties | 5 nearest counties | 8 nearest counties |
| ngr | 0.0333** | 0.0301** | 0.0209** |
| | (0.0148) | (0.0145) | (0.0092) |
| W×ngr | 0.0896*** | 0.1134*** | 0.1418*** |
| | (0.0196) | (0.0214) | (0.0239) |
| lnpop | 0.0028 | −0.0001 | −0.0011 |
| | (0.0139) | (0.0143) | (0.0144) |
| TS | −0.0197 | −0.0153 | −0.0120 |
| | (0.0185) | (0.0183) | (0.0182) |
| lnpgdp | 0.1243*** | 0.1251*** | 0.1277*** |
| | (0.0179) | (0.0171) | (0.0167) |
| lnpgdp2 | −0.0054*** | −0.0054*** | −0.0055*** |
| | (0.0009) | (0.0009) | (0.0009) |
| fd | −0.0167*** | −0.0161*** | −0.0156*** |
| | (0.0054) | (0.0054) | (0.0054) |
| gov | 0.1328*** | 0.1354*** | 0.1330*** |
| | (0.0292) | (0.0288) | (0.0284) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| N | 13693 | 13947 | 14050 |
| adj. R2 | 0.998 | 0.998 | 0.998 |

$$\tilde{w}_{ij,t}^{(K)}=\frac{q_{ij}^{(K)}I(ngr_{jt}\text{observable})}{\sum_{l\neq i}q_{il}^{(K)}I(ngr_{lt}\text{observable})} \tag{6}$$

Here, *I(·)* is an indicator function: it takes the value 1 when the corresponding adjacent counties have valid non-grain cultivation rate observations for year *t*, and 0 otherwise. If none of the *K* pre-determined adjacent counties have valid non-grain cultivation rate observations for year *t*, the spatial lag term for that county-year combination is marked as missing and excluded from the corresponding spatial model.

Table **5** reports the estimation results of the spatial models. Columns (1) through (3) use 3-neighbor, 5-neighbor, and 8-neighbor spatial weighting matrices, respectively. The estimated coefficients for the county's non-grain crop ratio do not differ significantly and are all statistically significant at the 5% level. The estimated coefficients for the non-grain crop ratio of adjacent counties (*W* × *ngr*) are 0.0896, 0.1134, and 0.1418, respectively, All three estimates are significant at the 1% statistical level, indicating that the positive spatial relationship between non-grain cultivation in neighboring counties and agricultural carbon emissions in the county under study does not depend on any specific choice among the 3-neighbor, 5-neighbor, or 8-neighbor matrices.

## 5.4. Heterogeneity Analysis

### *5.4.1. Major Grain-Producing Areas and Non-Major Producing Areas*

Table **6** shows that the coefficient on the non-grain conversion rate is significantly positive in major grain-producing areas, but significantly negative in non-major producing areas. Column (3) further reports the pooled interaction model. The coefficient on ngr is -0.0898 and significant at the 1% level, whereas the coefficient on *ngr×major* is 0.0297 and statistically significant. This difference indicates that the environmental

**Table 6: Heterogeneity Analysis: Major Grain-Producing Areas**

| lnCO2 | (1) | (2) | (3) |
|---|---|---|---|
| | Major | Non-major | Full |
| ngr | 0.0740*** | -0.0419*** | -0.0898*** |
| | (0.0076) | (0.0151) | (0.0306) |
| ngr×major | | | 0.0297** |
| | | | (0.0142) |
| lnpop | 0.0482*** | -0.0679*** | -0.0007 |
| | (0.0076) | (0.0173) | (0.0143) |
| TS | 0.0147 | -0.0723*** | -0.0172 |
| | (0.0110) | (0.0191) | (0.0188) |
| lnpgdp | 0.0743*** | 0.1220*** | 0.1256*** |
| | (0.0100) | (0.0228) | (0.0170) |
| lnpgdp2 | -0.0026*** | -0.0057*** | -0.0055*** |
| | (0.0005) | (0.0012) | (0.0009) |
| fd | -0.0182*** | 0.0065 | -0.0177*** |
| | (0.0040) | (0.0078) | (0.0054) |
| gov | 0.1893*** | 0.0499** | 0.1402*** |
| | (0.0192) | (0.0195) | (0.0288) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| _cons | 8.2033*** | 8.1919*** | 8.0471*** |
| | (0.0640) | (0.1298) | (0.0999) |
| N | 8456 | 5636 | 14092 |
| adj. R2 | 0.999 | 0.998 | 0.998 |

consequences of non-grain conversion depend on regional functional positioning and the existing production system. In major grain-producing areas, non-grain conversion typically means transitioning from relatively stable grain production systems to higher-input-intensity cash crops or protected agriculture, and is therefore more likely to increase emissions. At the same time, because major grain-producing areas originally bear national food security functions, non-grain conversion not only changes crop structure but may also alter existing large-scale, mechanized, and standardized production systems. The negative coefficient in non-major producing areas suggests that non-grain conversion in some regions may not represent high-input expansion, but rather low-input cash crop substitution, agricultural scale contraction, or structural adjustments against a background of originally low-efficiency grain production. For major producing areas, non-grain conversion governance should emphasize high-quality arable land use, large-scale grain production systems, and green input constraints; for non-major producing areas, policies should distinguish between high-carbon non-grain conversion and low-carbon crop adjustments, avoiding treating all cash crop development as negative behavior.

#### 5.4.2. Cultivated Land Type

Table **7** indicates that the coefficient on the non-grain conversion rate is significantly positive in southern paddy field regions, but significantly negative in northern dryland regions. Column (3) further reports the interaction model. The coefficient on ngr is -0.0238 and significant at the 5% level, while the coefficient on *ngr×southern* is 0.2547 and significant at the 1% level, confirming that the marginal association between non-grain conversion and emissions is significantly stronger in southern paddy field regions than in northern dryland regions. The two coefficients have opposite signs, providing empirical evidence for the difference between paddy fields and dryland farming, which is consistent with existing research evidence closely linking paddy ecosystems to methane emissions

**Table 7: Heterogeneity Analysis: Cultivated Land Type**

| lnCO2 | (1) | (2) | (3) |
|---|---|---|---|
| | Southern | Northern | Full |
| ngr | 0.1020*** | -0.0104*** | -0.0238** |
| | (0.0170) | (0.0022) | (0.0119) |
| ngr×southern | | | 0.2547*** |
| | | | (0.0393) |
| lnpop | -0.0424*** | 0.0001 | 0.0008 |
| | (0.0158) | (0.0039) | (0.0150) |
| TS | -0.0126 | 0.0042 | -0.0202 |
| | (0.0226) | (0.0035) | (0.0188) |
| lnpgdp | 0.1996*** | -0.0027 | 0.1274*** |
| | (0.0241) | (0.0028) | (0.0170) |
| lnpgdp2 | -0.0104*** | 0.0003* | -0.0057*** |
| | (0.0012) | (0.0001) | (0.0009) |
| fd | -0.0018 | -0.0010 | -0.0200*** |
| | (0.0082) | (0.0010) | (0.0054) |
| gov | 0.0776*** | 0.0076* | 0.1282*** |
| | (0.0252) | (0.0040) | (0.0297) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| _cons | 8.0570*** | 8.6519*** | 8.0220*** |
| | (0.1425) | (0.0173) | (0.0987) |
| N | 6636 | 7456 | 14092 |
| adj. R2 | 0.997 | 1.000 | 0.998 |

and irrigation management (Tian *et al*., 2020). Non-grain conversion in paddy field regions may involve aquatic cash crops, protected agriculture, or high-frequency multiple cropping, changes that may increase irrigation, energy, and agricultural input use. Paddy field ecosystems themselves are also closely related to methane emissions, irrigation and drainage management, and soil moisture conditions, making crop transitions more likely to bring complex emission consequences. In dryland regions, drought-resistant cash crop substitution, reduced chemical fertilizer input, or crop structure optimization scenarios may exist. Especially in certain northern regions, if non-grain conversion shifts toward oil crops, legumes, or other lower water-demand crops, the resource input intensity may not necessarily exceed that of the original grain production. Therefore, cultivated land moisture conditions and crop suitability are important dimensions for explaining the environmental effects of non-grain conversion. Non-grain conversion governance cannot make “one-size-fits-all” judgments divorced from paddy fields, drylands, and regional ecological conditions.

### ***5.4.3. Yangtze River Economic Belt***

The Yangtze River Economic Belt combines grain production, cash crop cultivation, and ecological security functions, with prominent water resource conditions, industrial foundations, and ecological sensitivity. Non-grain conversion in this region may be accompanied by expansion of fruit and vegetable, tea, floriculture, protected agriculture, and aquaculture-related land uses, thereby changing input intensities and emission structures. Compared with general regions, agricultural transitions in the Yangtze River Economic Belt are often simultaneously influenced by urban market demand, rural industrial upgrading, ecological protection, and watershed governance constraints (Luo *et al*., 2020; Sun *et al*., 2022), making it an important region for observing the carbon emission effects of non-grain conversion.

Table **8** shows that the coefficients on the non-grain conversion rate are significantly positive for both the Yangtze River Economic Belt and non-Yangtze River Economic Belt regions, but the coefficient is larger for the

**Table 8: Heterogeneity Analysis: Yangtze River Economic Belt**

| lnCO2 | (1) | (2) | (3) |
|---|---|---|---|
| | **Yangtze River** | **Non-Yangtze River Economic** | **Full** |
| ngr | 0.1631$^{***}$ | 0.0253$^{***}$ | 0.0319$^{**}$ |
| | (0.0189) | (0.0080) | (0.0149) |
| ngr×Yangtze River | | | 0.2247$^{***}$ |
| | | | (0.0370) |
| lnpop | 0.0556$^{***}$ | -0.0027 | 0.0020 |
| | (0.0179) | (0.0095) | (0.0141) |
| TS | 0.0673$^{**}$ | -0.0557$^{***}$ | -0.0307 |
| | (0.0317) | (0.0126) | (0.0188) |
| lnpgdp | 0.1259$^{***}$ | 0.1067$^{***}$ | 0.1147$^{***}$ |
| | (0.0287) | (0.0105) | (0.0171) |
| lnpgdp2 | -0.0053$^{***}$ | -0.0048$^{***}$ | -0.0051$^{***}$ |
| | (0.0014) | (0.0005) | (0.0009) |
| fd | -0.0439$^{***}$ | -0.0178$^{***}$ | -0.0191$^{***}$ |
| | (0.0103) | (0.0040) | (0.0055) |
| gov | 0.2964$^{***}$ | 0.1204$^{***}$ | 0.1439$^{***}$ |
| | (0.0396) | (0.0152) | (0.0285) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| _cons | 8.0456$^{***}$ | 8.0765$^{***}$ | 8.0934$^{***}$ |
| | (0.1720) | (0.0664) | (0.0987) |
| N | 3972 | 10120 | 14092 |
| adj. R2 | 0.996 | 0.999 | 0.998 |

Yangtze River Economic Belt. In Column (3), the coefficient on *ngr* is 0.0319 and significant at the 5% level, while the coefficient on *ngr*×*Yangtze River* is 0.2247 and significant at the 1% level, confirming that the positive marginal association is significantly larger within the Yangtze River Economic Belt. This indicates that in ecologically sensitive regions with higher cash crop proportions and more concentrated agricultural inputs, the positive correlation between non-grain conversion and agricultural carbon emissions is stronger. This result supports the implementation of more refined cropping structure guidance in key watersheds and ecological functional areas. Specifically, non-grain conversion governance in the Yangtze River Economic Belt should not focus only on whether arable land is occupied, but also on crop types, irrigation methods, protected agriculture energy consumption, plastic film use, and chemical fertilizer and pesticide inputs. If policies only control grain area while neglecting input intensity, the coordinated goals of food security and agricultural emission reduction may be difficult to achieve. If non-grain conversion increases chemical fertilizer, pesticide, and protected facility energy use, it may simultaneously bring carbon emission and water environment pressures. Therefore, the Yangtze River Economic Belt particularly needs cross-regional joint prevention and control and unified low-carbon agricultural technical standards.

### 5.4.4. Stage of Economic Development

Economic development level affects farmers' crop choices, agricultural capital inputs, availability of machinery services, and local governments' environmental governance capacity (Luo *et al*., 2017; Zhang *et al*., 2019). This paper uses the median of per capita regional gross domestic product to divide counties into high-development and low-development groups to examine whether non-grain conversion effects vary with development stage.

Table **9** shows that the coefficient on the non-grain conversion rate is significantly positive in high-development counties, but significantly negative in low-

**Table 9: Heterogeneity Analysis: Stage of Economic Development**

| lnCO2 | (1) | (2) | (3) |
|---|---|---|---|
| | High | Low | Full |
| ngr | 0.0674*** | -0.0476*** | -0.0335** |
| | (0.0127) | (0.0096) | (0.0141) |
| ngr×high | | | 0.0678*** |
| | | | (0.0080) |
| lnpop | 0.0230** | -0.0098 | 0.0001 |
| | (0.0099) | (0.0147) | (0.0140) |
| TS | -0.0616 | 0.0388*** | -0.0400** |
| | (0.0420) | (0.0135) | (0.0185) |
| lnpgdp | 0.4221*** | -0.1238*** | |
| | (0.0389) | (0.0264) | |
| lnpgdp2 | -0.0181*** | 0.0085*** | 0.0001 |
| | (0.0017) | (0.0015) | (0.0002) |
| fd | -0.0131** | 0.0079 | -0.0163*** |
| | (0.0054) | (0.0064) | (0.0053) |
| gov | 0.1134*** | 0.1059*** | 0.1701*** |
| | (0.0338) | (0.0183) | (0.0299) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| _cons | 5.9549*** | 9.3674*** | 8.7257*** |
| | (0.2336) | (0.1246) | (0.0617) |
| N | 5002 | 9005 | 14092 |
| adj. R2 | 0.999 | 0.998 | 0.998 |

development counties. In Column (3), the coefficient on *ngr* is -0.0335 and significant at the 5% level, while the coefficient on *ngr×high* is 0.0678 and significant at the 1% level. Non-grain conversion in high-development counties is more likely oriented toward high-value-added, protected, and capital-intensive crops, thereby increasing energy and agricultural input use; low-development counties may have low-input cash crop substitution or smaller-scale non-grain conversion. Non-grain conversion governance needs to be combined with development stage rather than adopting a single standard. For high-development counties, policy priorities should focus on constraining high-input protected agriculture, promoting green input substitution, and improving energy efficiency; for low-development counties, policies should identify whether non-grain conversion truly damages grain production capacity and ecological efficiency, avoiding simplistically including low-input, ecologically friendly crop adjustments in high-pressure regulation. Economic development does not automatically bring agricultural greening; after capital, technology, and markets enter agriculture, they may improve efficiency or may promote higher-input, higher-value-added, but higher-emission production models.

### 5.4.5. Population Scale

Table **10** shows that the coefficients on the non-grain conversion rate are significantly positive in both large-population and small-population counties, but the coefficient is higher in large-population counties. Also, Column (3) reinforces this conclusion in the full sample. The coefficient on *ngr* is 0.0593 and significant at the 1% level, while the coefficient on *ngr×large* is 0.0677 and significant at the 1% level, indicating that the emission-enhancing association is significantly larger in large-population counties. Large-population areas typically face stronger agricultural product market demand and land scarcity constraints, and agricultural production tends toward higher-value-added and higher-input structures, thereby amplifying the emission effects of non-grain

**Table 10: Heterogeneity Analysis: Population Scale**

| lnCO2 | (1) | (2) | (3) |
|---|---|---|---|
| | Large | Small | Full |
| ngr | 0.1209*** | 0.0465*** | 0.0593*** |
| | (0.0153) | (0.0087) | (0.0143) |
| ngr×large | | | 0.0677*** |
| | | | (0.0149) |
| lnpop | 0.0033 | 0.0078 | -0.0074 |
| | (0.0168) | (0.0092) | (0.0141) |
| TS | -0.0419* | -0.0116 | -0.0211 |
| | (0.0224) | (0.0130) | (0.0188) |
| lnpgdp | 0.1009*** | 0.0992*** | 0.1208*** |
| | (0.0209) | (0.0121) | (0.0171) |
| lnpgdp2 | -0.0040*** | -0.0043*** | -0.0053*** |
| | (0.0011) | (0.0006) | (0.0009) |
| fd | -0.0251*** | -0.0058 | -0.0173*** |
| | (0.0061) | (0.0045) | (0.0054) |
| gov | 0.3546*** | 0.1003*** | 0.1447*** |
| | (0.0381) | (0.0151) | (0.0287) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| _cons | 8.6499*** | 7.6304*** | 8.0933*** |
| | (0.1280) | (0.0720) | (0.0985) |
| N | 6945 | 7120 | 14092 |
| adj. R2 | 0.996 | 0.999 | 0.998 |

conversion (van Beek *et al*., 2010; Tilman *et al*., 2011). For large-population counties, agricultural emission reduction policies need to be combined with urban peripheral agriculture, "vegetable basket" projects, and protected agriculture governance. These products have strong market returns but may also depend more intensively on protected facilities, cold chain systems, and inputs.

## 6. FURTHER ANALYSIS: MECHANISM TESTS

To explain the possible channels through which non-grain conversion affects agricultural carbon emissions, this paper conducts mechanism tests from two aspects: agricultural mechanization and scale management, and the proportion of cash crop cultivation. Due to the difficulty of obtaining complete county-level statistics on detailed inputs such as chemical fertilizers, pesticides, plastic film, diesel fuel, and irrigation energy consumption, this paper selects total agricultural machinery power and the proportion of cash crop cultivation as observable mechanism variables, respectively characterizing mechanization efficiency and production behavior adjustments. However, conventional step-by-step mediation regressions are sensitive to measurement error and unobserved confounding in the channel variables. Therefore, this paper interprets the mechanism analysis results as correlational evidence consistent with the theoretical hypotheses rather than as definitive proof of causal transmission pathways.

The mechanism test models are as follows:

$$Z_{it}=\theta ngr_{it}+\mu control_{it}+\mu_i+\delta_t+\varepsilon_{it} \quad (7)$$

$$lnCO2_{it}=\rho_1 Z_{it}+\rho_2 ngr_{it}+\sigma control_{it}+\mu_i+\delta_t+\varepsilon_{it} \quad (8)$$

In Equations (7) and (8), the mechanism variables are total agricultural machinery power and the proportion of cash crop cultivation, respectively; other variable definitions are consistent with the baseline model.

**Table 11: Mechanism Analysis: Agricultural Mechanization and Scale Management Mechanism**

| | (1) | (2) | (3) |
|---|---|---|---|
| | *lnCO2* | *am* | *lnCO2* |
| *ngr* | 0.0716*** | -8.4175*** | 0.0605*** |
| | (0.0073) | (1.3046) | (0.0072) |
| *am* | | | -0.0002*** |
| | | | (0.0000) |
| *lnpop* | -0.0007 | -3.8928*** | 0.0231*** |
| | (0.0070) | (1.2733) | (0.0070) |
| *TS* | -0.0194 | -20.3298*** | -0.0257** |
| | (0.0118) | (2.0936) | (0.0116) |
| *lnpgdp* | 0.1226*** | 30.7873*** | 0.1150*** |
| | (0.0108) | (1.9164) | (0.0106) |
| *lnpgdp2* | -0.0054*** | -1.5943*** | -0.0050*** |
| | (0.0005) | (0.0937) | (0.0005) |
| *fd* | -0.0177*** | -7.1806*** | -0.0192*** |
| | (0.0041) | (0.7315) | (0.0040) |
| *gov* | 0.1422*** | -14.3521*** | 0.1388*** |
| | (0.0095) | (1.7274) | (0.0095) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| *_cons* | 8.0633*** | -88.1016*** | 8.0497*** |
| | (0.0672) | (11.9156) | (0.0657) |
| *N* | 14092 | 13481 | 13460 |
| *adj. R2* | 0.998 | 0.923 | 0.998 |

### 6.1. Mechanism of Agricultural Mechanization and Scale Management

Table **11** shows that the coefficient of the non-grain conversion rate on total agricultural machinery power is significantly negative, while the coefficient of total agricultural machinery power on carbon emissions is significantly negative when entered into the carbon emissions equation, and the coefficient on the non-grain conversion rate decreases from 0.0716 to 0.0605. As a supplement, Table **13** reports a county-clustered bootstrap test with 1,000 resamples. The estimated indirect effect is 0.0019, with a bias-corrected 95% confidence interval of [0.0002, 0.0052], which excludes zero, indicating statistical significance. However, it accounts for only approximately 3.0% of the total effect and is therefore a secondary transmission channel. This indicates that non-grain conversion may create indirect emission pressures by weakening large-scale mechanization inputs or reducing mechanization efficiency advantages. Further analysis shows that grain crop production typically has strong standardization and mechanization adaptability, while cash crop production often relies more on refined labor or specialized machinery during sowing, field management, and harvesting. If non-grain conversion leads to decreased efficiency of general machinery services, county-level agriculture may experience increased total emissions or decreased emission efficiency per unit of output. This finding has direct policy implications: promoting agricultural mechanization itself does not necessarily conflict with emission reduction goals; the key lies in whether mechanization matches crop structure and management scale. If non-grain conversion leads to fragmentation of standardized operation systems, low-carbon agricultural machinery and socialized services need to be upgraded synchronously with crop structure adjustments. Otherwise, agricultural modernization may lose efficiency during structural transitions.

**Table 12: Mechanism Analysis: Cash Crop Cultivation Proportion Mechanism**

| | (1) | (2) | (3) |
|---|---|---|---|
| | ***lnCO2*** | ***crop*** | ***lnCO2*** |
| ngr | 0.0716*** | 0.2860*** | 0.0494*** |
| | (0.0073) | (0.0065) | (0.0145) |
| crop | | | 0.1061*** |
| | | | (0.0247) |
| lnpop | -0.0007 | 0.0329*** | -0.0334*** |
| | (0.0070) | (0.0062) | (0.0122) |
| TS | -0.0194 | -0.0018 | 0.0511*** |
| | (0.0118) | (0.0091) | (0.0175) |
| lnpgdp | 0.1226*** | 0.0521*** | 0.1129*** |
| | (0.0108) | (0.0088) | (0.0174) |
| lnpgdp2 | -0.0054*** | -0.0023*** | -0.0047*** |
| | (0.0005) | (0.0004) | (0.0009) |
| fd | -0.0177*** | -0.0207*** | -0.0280*** |
| | (0.0041) | (0.0036) | (0.0070) |
| gov | 0.1422*** | -0.0058 | 0.1570*** |
| | (0.0095) | (0.0098) | (0.0194) |
| County Effect | YES | YES | YES |
| Time Effect | YES | YES | YES |
| _cons | 8.0633*** | -0.4297*** | 8.5232*** |
| | (0.0672) | (0.0550) | (0.1082) |
| N | 14092 | 6985 | 6985 |
| adj. R2 | 0.998 | 0.922 | 0.996 |

### 6.2. Mechanism of Cash Crop Cultivation Proportion

Table **12** shows that the non-grain conversion rate significantly increases the proportion of cash crop cultivation; when the proportion of cash crops is simultaneously included, the coefficient of cash crop proportion on agricultural carbon emissions is significantly positive, and the coefficient on the non-grain conversion rate decreases from 0.0716 to 0.0494. Similarly, Table **13** reports a county-clustered bootstrap test with 1,000 resamples for the cash-crop cultivation share. The indirect effect through the cash-crop channel is 0.0303, with a bias-corrected 95% confidence interval of [0.0086, 0.0588], which excludes zero and accounts for approximately 38.0% of the total effect. This indicates that the shift in crop composition toward cash crops is the main transmission channel through which non-grain conversion affects agricultural carbon emissions. This may be because when local agricultural transitions emphasize income growth and specialty industries, farmers are more likely to choose crops with higher returns but more intensive inputs; if green production technologies, low-carbon agricultural inputs, and input constraints do not keep pace, cash crop expansion may bring emission pressures. Non-grain conversion governance should not look only at area proportions, but also at what is planted after non-grain conversion, how it is planted, and how much input is used. If cash crops depend on high chemical fertilizers, high pesticides, and high-energy protected facilities, emission pressures are greater; however, if input intensity is reduced through green prevention and control, water-saving irrigation, and organic substitution, the environmental consequences of non-grain conversion may also improve.

**Table 13: Bootstrap Tests of Indirect Effects**

| | (1) | (2) |
|---|---|---|
| | ***am*** | ***crop*** |
| Indirect effect | 0.0019 | 0.0303 |
| | [0.0002, 0.0052] | [0.0086, 0.0588] |
| Direct effect | 0.0605 | 0.0494 |
| | [0.0348, 0.0882] | [-0.0004, 0.0933] |
| Total effect (c) | 0.0624 | 0.0798 |
| | [0.0354, 0.0896] | [0.0370, 0.1202] |
| Proportion mediated | 0.030 | 0.380 |
| | [0.003, 0.086] | [0.101, 1.024] |

**Notes:** Bias-corrected (BC) 95% confidence intervals are reported in square brackets.

### 6.3. Moderating Effects of Fiscal Constraints

To examine whether local fiscal constraints alter the relationship between land conversion from grain production and agricultural carbon emissions, this paper employs the following moderation effect model:

$$lnCO_{2it} = \alpha + \beta_1 ngr_{it} + \beta_2 Z^c_{it} + \beta_3(ngr_{it} \times Z^c_{it}) + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

Here, $Z^c_{it}$ represents the fiscal constraint indicator after centering, and $ngr_{it} \times Z^c_{it}$ is the interaction term. If $\beta_3$ is significantly positive, it indicates that the higher the value of the fiscal indicator, the stronger the positive relationship between non-grain cultivation and agricultural carbon emissions; if $\beta_3$ is not significant, it suggests that the data do not provide evidence that the fiscal indicator systematically alters the marginal relationship with non-grain cultivation.

This study uses local fiscal pressure (*fp*) and local fiscal decentralization (*fd*) as fiscal constraint indicators. Local fiscal pressure is defined as the ratio of fiscal budget expenditures to fiscal budget revenues, while fiscal decentralization adopts the definition provided in the control variables. Observations where the ratio of fiscal revenue to fiscal expenditure is non-positive are treated as missing to avoid the calculation of invalid reciprocals. Subsequently, this study trims fiscal pressure at the 1% and 99% quantiles to reduce the influence of extreme ratios arising when fiscal revenue approaches zero. Before constructing interaction terms, fiscal pressure and fiscal decentralization are centered on the sample median. Fiscal pressure and fiscal decentralization are constructed using the same fiscal revenue and fiscal expenditure variables but in opposite directions.

Table **14** reports the results of the moderating effects of fiscal constraints, with Column (1) using fiscal pressure and Column (2) using fiscal decentralization. In Columns (1) and (2), the estimated coefficients for the non-grain cultivation rate (*ngr*) are both significant at the 1% level, indicating that under fiscal pressure, a significant positive relationship still exists between non-grain cultivation and agricultural carbon emissions. Furthermore, in Column (1), the estimated coefficient for the interaction term with fiscal pressure is 0.0010, and the estimated coefficient for fiscal pressure itself is 0.0009; both are positive at the 5% significance level. In Column (2), the estimated coefficient for the interaction term with fiscal decentralization is −0.0144 at the 10% significance level. The estimated coefficient for fiscal decentralization itself is −0.0131, which is significant at the 5% level, indicating that local fiscal constraints significantly strengthen the relationship between non-grain crop cultivation and agricultural carbon emissions.

**Table 14: Moderating Effects of Fiscal Constraints**

| $lnCO_2$ | (1) | (2) |
|---|---|---|
| | fp | fd |
| ngr | 0.0736*** | 0.0733*** |
| | (0.0082) | (0.0088) |
| ngr×fp | 0.0010** | |
| | (0.0004) | |
| fp | 0.0009** | |
| | (0.0004) | |
| ngr×fd | | -0.0144* |
| | | (0.0080) |
| fd | | -0.0131** |
| | | (0.0054) |
| lnpop | -0.0023 | -0.0009 |
| | (0.0083) | (0.0083) |
| TS | -0.0219* | -0.0196* |
| | (0.0116) | (0.0117) |
| lnpgdp | 0.1222*** | 0.1225*** |
| | (0.0105) | (0.0105) |
| lnpgdp2 | -0.0055*** | -0.0054*** |
| | (0.0005) | (0.0005) |
| gov | 0.1370*** | 0.1416*** |
| | (0.0158) | (0.0154) |
| County Effect | YES | YES |
| Time Effect | YES | YES |
| N | 14092 | 14092 |
| adj. R2 | 0.603 | 0.998 |

## 7. CONCLUSIONS AND POLICY IMPLICATIONS

Based on China's county-level unbalanced panel data, this paper examines the relationship between non-grain conversion of cropping structure and agricultural carbon emissions. The findings indicate that, after controlling for county fixed effects and year fixed effects, the non-grain conversion rate is significantly and positively correlated with agricultural carbon emissions. This result remains generally robust after endogeneity treatment, winsorization, alternative measures, and adjustments to clustering levels. Heterogeneity analysis shows that the emission effects of non-grain conversion are stronger in major grain-producing areas, southern paddy field regions, the Yangtze River Economic Belt, counties with higher development levels, and counties with larger populations, while exhibiting different directions in some non-major producing areas, dryland regions, and counties with lower development levels. In non-major grain-producing areas, northern dryland regions, and counties with lower development levels, non-grain adjustments are associated with declines in agricultural carbon emissions, indicating that non-grain conversion is not inherently carbon-intensive in all contexts. Under specific regional conditions and production methods, appropriate structural adjustment may instead yield emission reductions or environmental benefits. Mechanism tests indicate that increased cash crop cultivation proportions and weakened mechanization efficiency advantages may be important channels through which non-grain conversion affects agricultural carbon emissions.

Based on the above conclusions, this paper proposes the following policy implications:

First, implement differentiated non-grain conversion governance by zone and category. Major grain-producing areas, southern paddy field regions, and the Yangtze River Economic Belt should focus on preventing disorderly expansion of high-input, high-energy non-grain uses, and quantitative thresholds can be established along three dimensions: (1) Input intensity. Using per-unit-area fertilizer, pesticide, agricultural film, irrigation water, and electricity consumption as core indicators, non-grain crop types for which any indicator is significantly higher than under the original grain production system, or exceeds the local average for major grain varieties by a specified margin, should be classified as high-input non-grain conversion; those with input levels broadly comparable to or lower than grain cultivation should be classified as low-input non-grain conversion. (2) Cultivation practices. Any use pattern involving damage to the topsoil, ground hardening, year-round plastic mulching, high-frequency multiple cropping, or flood irrigation should be categorized as high-input and high-risk. (3) Ecological impacts. Classification should be calibrated according to whether permanent basic farmland is occupied, whether the land is located in an ecologically sensitive area, and whether the use retains a carbon-sink function. On this basis, county-level classification catalogues for non-grain conversion should be compiled and regularly updated in response to changes in crops and agronomic practices, so that regulation and guidance follow unified and transparent operational standards. Meanwhile, non-major producing areas and dryland regions should combine ecological suitability to guide low-input, low-emission planting structure adjustments that do not damage the food security baseline. For non-major grain-producing areas and northern dryland regions, low-input non-grain conversion should be proactively guided through positive lists, technical support, and green certification, thereby cultivating it as a potential pathway for structural emission reduction.

Second, integrate food security assessment with agricultural carbon emission reduction assessment. Local governments should not stop at formalized cultivated land use management, but should also pay attention to changes in chemical fertilizer, pesticide, plastic film, irrigation, and energy inputs resulting from crop conversion. In specific implementation, differentiated governance by zone and category should establish a system with both negative lists and positive guidance. Non-grain conversion that damages tillage layers, increases high-carbon inputs, or affects permanent basic farmland grain functions should be strictly restricted, while ecologically friendly, low-input crop adjustments that do not damage the food security baseline can be guided through technical standards and green certification.

Third, combine non-grain conversion governance with the promotion of low-carbon agricultural technologies. Promote the application of technologies such as soil-testing formula fertilization, green prevention and control, energy-saving agricultural machinery, water-saving irrigation, and plastic film recycling. For regions that have already formed cash crop industry advantages, emission intensity should be reduced through green certification, low-carbon agricultural input subsidies, and agricultural technical services, rather than simply compressing all non-grain crops.

Fourth, improve the efficiency of scaled agricultural management and mechanization services. For areas where crop conversion leads to decreased mechanization adaptability, socialized agricultural machinery services, crop-specific machinery, and low-carbon protected agriculture equipment should be developed to prevent non-grain conversion from bringing production fragmentation and redundant inputs. Especially in major grain-producing areas, contiguous cultivation, scale management, and agricultural machinery service systems should be maintained to prevent non-grain conversion from undermining the efficiency foundation of grain production systems.

Fifth, establish a county-level non-grain conversion and agricultural carbon emission joint monitoring system. Currently, many localities' monitoring of non-grain conversion still focuses on area and use changes, with insufficient attention to input intensity, crop types, and emission outcomes. A county-level joint database of crop structure, agricultural inputs, and carbon emissions should be established based on statistical data, remote sensing identification, and agricultural business entity reporting.

Sixth, improve ecological compensation and transition incentives in key regions. For areas with stronger non-grain conversion emission effects such as the Yangtze River Economic Belt, southern paddy field regions, and major grain-producing areas, the adoption of low-carbon agricultural technologies, plastic film recycling, chemical fertilizer and pesticide reduction, and water-saving irrigation should be incorporated into compensation or reward systems, providing practical incentives for farmers while avoiding crude “one-size-fits-all” governance. The monitoring system should also serve policy evaluation. Only by continuously tracking changes in county-level crop structure, input intensity, and emissions can it be determined whether non-grain conversion control truly reduces environmental pressures. For regions with emission-reduction potential, such as some non-major grain-producing areas, dryland regions, and counties with lower development levels, ecological compensation and transition incentives should also cover low-input non-grain transitions themselves, so that policy design achieves a balance between restriction and incentive.

This paper still has limitations. Constrained by data availability, mechanism variables can only characterize partial input channels, and it is difficult to fully identify the specific contributions of chemical fertilizers, pesticides, irrigation, and other inputs; the lagged one-period instrumental variable also cannot completely exclude all dynamic omitted variables. Future research can combine remote sensing crop identification, farmer surveys, and more detailed input data to further identify the true carbon emission mechanisms of different non-grain conversion types, and can also combine policy shocks or natural suitability instrumental variables to further improve causal identification strength. In addition, this paper does not directly distinguish between $CO_2$, methane, and nitrous oxide in the agricultural sector, nor does it precisely decompose emissions to specific crops. In the future, finer-scale crop identification and greenhouse gas accounting data can be obtained to determine which non-grain conversion types are truly high-carbon and which are merely risks in the food security sense rather than high-emission in the environmental sense.

## CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Xinyi Yan: Writing -original draft, Investigation, Data curation, Conceptualization, Formal analysis.

## DECLARATION OF COMPETING INTEREST

The author declares that she has no conflicts of interest related to this work.

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