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# Rural labor transfer, non-farm income and agricultural non-point source pollution: evidence from China

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The prevention and control of agricultural non-point source pollution (ANPP) is vital for promoting green agricultural development and has become a key public concern. Using statistical data from 30 provinces in China during 2005–2022, this study empirically investigates the influence mechanism and threshold effects of rural labor transfer on ANPP, employing a comprehensive framework including benchmark regression, mediating-moderating effect models, and threshold regression, supplemented by instrumental variable (IV) techniques to address endogeneity. Key findings include: (i) Rural labor transfer significantly exacerbates ANPP, with heterogeneous effects across rural labor transfer types and regional contexts. (ii) A single threshold effect exists, demonstrating a non-linear pattern where the marginal impact of rural labor transfer on ANPP diminishes as its scale increases. (iii) Non-farm income serves as a critical mediating pathway through which rural labor transfer intensifies ANPP. (iv) Agricultural socialized services moderate this effect by mitigating the mediating role of non-farm income, thereby alleviating environmental degradation. These findings provide policy insights for China to optimize ANPP prevention strategies, highlighting the need to coordinate labor migration management, income diversification, and agricultural socialized services development for sustainable agricultural growth.

KEYWORDS

**rural labor transfer, agricultural non-point source pollution, non-farm income, agricultural socialized services, pesticides and fertilizers, threshold effects**

## 1 Introduction

The uneven spatial distribution of natural resources has historically driven rural labor migration for improved livelihoods (Gray and Bilsborrow, 2014; Gartaula et al., 2012). Meanwhile, the acceleration of modern industrialization and urbanization in China has intensified the flow of rural labor from agriculture to urban industries, leading to agricultural labor shortages. This shift has prompted increased inputs of chemical fertilizers and pesticides to maintain productivity, yet China's annual fertilizer consumption exceeds 600,000 tons, with a utilization rate of only 40.2% for major crops in 2020 (Lin and Ma, 2013; Wang et al., 2022; Hou and Yao, 2019; Yu et al., 2022). Excessive application and inefficient use of agrochemicals have made ANPP a primary threat to water and soil ecosystems, undermining food safety and sustainable development (Shou et al., 2019; Fischer et al., 2010; Li et al., 2022; Liu et al., 2023; Yu, 2018).

The Chinese government attaches great importance to the prevention and control of ANPP at the policy level. For instance, the Guidelines of the Ministry of Agriculture and Rural Affairs on Accelerating the Comprehensive Green Transformation of Agricultural Development and Promoting Rural Ecological Revitalization clearly states that efforts should be made to promote the reduction of agricultural inputs such as pesticides and chemical fertilizers. And the No. 1 Central Document of 2025 points out that it is necessary to strengthen the systematic governance of areas with prominent ANPP. Academically, existing studies have explored ANPP causes (Zhang et al., 2024; Min and Kong, 2016), prevention measures (Xue et al., 2020; Zhou et al., 2021; Zhang and Guo, 2021), influencing factors (Wang et al., 2022; Li et al., 2022; Badrzadeh et al., 2022) and risk assessment (Zhu et al., 2020; Li et al., 2023). Meanwhile, scholars have also paid attention to the social, economic and ecological environmental impacts brought about by the transfer of rural labor force (Liao et al., 2020; Xie and Jiang, 2016; Gao et al., 2020; Gai et al., 2023). In the composition of farmers' household income, the increase in non-farm income brought about by the transfer of labor force constitutes the main source of farmers' household income. Previous studies have shown that higher incomes could encourage the adoption of modern agricultural techniques and reduce reliance on traditional inputs (Zhong et al., 2016; Caulfield et al., 2019; Zhou et al., 2024). However, it also brings about some environmental problems at the same time. Especially in reality, farmers, in order to make up for part of the loss of agricultural income caused by the shortage of labor force, might overuse pesticides and fertilizers to maximize yields and economic returns (Shao et al., 2021), thereby unexpectedly exacerbating ANPP.

While these findings have provided some academic evidence for understanding the complex relationship between rural labor transfer and ANPP, the transition from theoretical recognition to practical prevention and control strategies reveals significant research gaps. Especially, some scholars have initially found that the transfer of rural labor force can change the traditional structure of agricultural input factors and increase the use of pesticides and fertilizers (Zhong et al., 2016; Zhang et al., 2017; Li et al., 2023), which is an important source of ANPP, and probably make their application efficiency reduced (Shao and Li, 2020). Therefore, exploring the causes of ANPP from the perspective of rural labor transfer may be an important direction for us to seek prevention and control methods for ANPP. However, research on the specific mechanisms through which rural labor transfer affects ANPP remains limited, particularly regarding the mediating role of non-farm income and the moderating effect of agricultural socialized services. Previous studies have identified a correlation between labor transfer and increased agrochemical use (Li et al., 2023; Guo et al., 2022; Li et al., 2022), but three critical gaps persist: first of all, most studies focus on the direct impact and ignore how non-farm income brought about by rural labor transfer changes farmers' input decisions. Second, the role of agricultural socialized services in pollution control has not been fully explored. Thirdly, the research lacks a systematic analysis of the differences in the impact of rural labor transfer among different economic zones in China.

This study integrates non-farm income and agricultural socialized services into a theoretical framework to examine labor transfer's impact on ANPP, using panel data from 30 Chinese provinces (2005–2022). By combining benchmark regression, mediating-moderating models, and threshold analysis, we aim to reveal the relationship between rural labor transfer and ANPP, quantify the mediating effect of non-farm income and the moderating role of agricultural socialized services and identify regional disparities in pollution mechanisms. Overall, this study will enrich the literature by disentangling the complex pathways through which labor migration influences ANPP, integrating economic (non-farm income) and sociological (agricultural socialized services) perspectives and findings will provide evidence-based policy recommendations for coordinating labor mobility, income diversification, and green agricultural development, supporting China's rural revitalization and ecological civilization strategies.

The remainder of the paper is structured as follows: Section 2 presents theoretical analysis and hypotheses; Section 3 details methods and data; Section 4 reports empirical results; Section 5 discusses results and limitations; Section 6 concludes with policy suggestions.

## 2 Theoretical analysis and research hypotheses

### 2.1 Rural labor transfer and ANPP

The theory of factor substitution posits that the migration of rural labor from agricultural production to non-farm sectors inevitably induces agricultural labor shortages, thereby adversely affecting production outcomes (Xie and Lu, 2017; Zhang et al., 2020; Zhang et al., 2021). As boundedly rational decision-making agents, farmers typically respond to this challenge by adopting modern agricultural technologies to maintain production stability. Specifically, they tend to intensify inputs of modern agricultural elements such as chemical fertilizers and pesticides to compensate for productivity losses caused by labor scarcity (Shi et al., 2016). Empirical observations reveal that migrant workers predominantly consist of younger, better-educated individuals, leaving behind an aging agricultural workforce characterized by limited awareness of ecological conservation and persistent reliance on extensive farming practices (Ashley et al., 2018). This demographic shift creates a propensity for excessive agrochemical application on remaining cultivated land, resulting in dual consequences of diminished production efficiency and environmental degradation. Simultaneously, rural labor outflow exerts upward pressure on agricultural wages through labor market tightening (Gallardo and Sauer, 2018). The resultant changes in relative factor prices create economic incentives for farmers to substitute relatively abundant production factors (e.g., chemical inputs and machinery) for scarce labor resources (Nguyen et al., 2019; Su et al., 2016). This substitution behavior manifests in increased procurement of yield-enhancing inputs including pesticides, fertilizers, and mechanization services (Guo et al., 2022), ostensibly aimed at improving production efficiency and maximizing agricultural income. However, such compensatory strategies carry significant environmental externalities. The persistent intensification of chemical inputs, while potentially effective in the short term, tends to culminate in the chronic over-application of agrochemicals. This practice constitutes a primary driver of ANPP, presenting critical challenges to sustainable agricultural development. Based on this theoretical framework and empirical evidence, Hypothesis 1 (H1) is formulated.

> *H1:* Rural labor transfer contributes to ANPP.

## 2.2 Rural labor transfer, non-farm income and ANPP

Rural labor transfer represents a significant phenomenon in the industrialization and urbanization processes of developing nations, particularly in China, where it exerts profound impacts on rural economic structures, farmers' income sources, and agricultural production patterns. From an economic perspective, rural labor transfer serves as a crucial mechanism for farmers to obtain non-farm income and enhance household earnings (Caulfield et al., 2019). The substantial increase in non-farm income has led to notable changes in farmers' production decisions and resource allocation, subsequently influencing ANPP. The primary economic effect of transfer manifests in the significant augmentation of non-farm income. According to data from China's National Bureau of Statistics, wage income constituted over 42% of farmers' household income in 2022, emerging as the principal driver of income growth. This diversification of income sources reduces reliance on singular agricultural income and enhances household economic resilience. Concurrently, it alleviates financial constraints in agricultural production, enabling farmers to invest more in chemical inputs such as pesticides and fertilizers, thereby compensating for labor shortages resulting from migration (Li et al., 2022; Luan et al., 2016). Furthermore, the increase in non-farm income has enhanced farmers' risk-bearing capacity, prompting a shift in cultivation patterns from traditional food crops to higher-value cash crops that require intensive chemical inputs (e.g., vegetables and fruits) (Luo, 2017; Yang et al., 2025). This transition has led to increased utilization of chemical substances in agricultural production. Moreover, the growth of non-farm income has facilitated the transformation of agricultural production from labor-intensive to capital-intensive modes. Farmers increasingly rely on agricultural mechanization and chemical inputs to enhance production efficiency, rather than traditional labor-intensive methods. While this transformation has improved agricultural productivity, it has simultaneously exacerbated ANPP through the intensified use of modern machinery and chemical inputs (Wu and Liu, 2017; Shao and Li, 2020). As a result, rural labor transfer, by increasing non-farm income, alters farmers' production decisions and resource allocation patterns, ultimately contributing to the aggravation of ANPP. Hence, Hypothesis 2 (H2) is proposed.

> *H2: Non-farm income* plays a mediating role in rural labor transfer affecting ANPP.

## 2.3 Non-farm income, agricultural socialized services and ANPP

Agricultural socialized services refer to a series of comprehensive services provided by multiple entities such as government public service institutions, enterprises, and social organizations for agricultural production and operation entities, covering the entire process from pre-production, production to post-production of agriculture. The rise in non-farm income enhances the overall household income level of farmers, enabling them to access diversified agricultural socialized services (Li et al., 2023; Yang et al., 2020). This development partially mitigates the issue of farmers relying exclusively on chemical inputs such as pesticides and fertilizers to compensate for declining agricultural productivity caused by labor shortages. In practice, various aspects of agricultural production can be outsourced to specialized service providers (Zhang and Luo, 2019), leading to a scenario where "professionals handle professional tasks." The procurement of agricultural socialized services offers significant cost advantages compared to the direct purchase of chemical inputs like pesticides and fertilizers. Consequently, driven by cost efficiency and higher profitability, households primarily dependent on non-farm income are more inclined to delegate the pre-production, production, and post-production stages of agriculture to third-party service organizations. Service providers, in delivering these services, tend to reduce the usage of chemicals such as pesticides and fertilizers to minimize input costs and maximize profits (Yang et al., 2020), thereby contributing to the reduction of ANPP. Additionally, service providers possess the advantage of accessing cutting-edge technology and market data. They can disseminate application standards, environmental awareness, and efficient pesticide and fertilizer application techniques to farmers through their services. This transfer of knowledge and skills has enhanced farmers' understanding and proficiency in the scientific application of pesticides and fertilizers, transforming their previous over-reliance on chemical inputs. Thus, the ANPP resulting from increased non-farm income can be alleviated. Based on this reasoning, Hypothesis 3 (H3) is proposed.

> *H3:* Agricultural socialized services inhibit the mediating effect of *non-farm income* in rural labor transfer affecting ANPP.

## 2.4 Threshold effect of rural labor transfer on ANPP

Rural labor transfer fundamentally represents a reallocation of household labor resources (Zhang et al., 2021). In the initial stages of rural labor transfer, when the scale remains limited, its impact on household labor division and income generation is relatively marginal, and the continuity of agricultural production can be maintained. However, as the magnitude of rural labor transfer expands and the depletion of household labor resources intensifies, significant transformations occur in agricultural production patterns. This transition manifests as a shift from labor-intensive agricultural practices to modern production factor-oriented approaches. Concurrently, agricultural producers increasingly resort to intensive application of chemical inputs, particularly pesticides and fertilizers, to ensure production stability and maintain income levels (Li et al., 2023). This practice has been empirically demonstrated to exacerbate ANPP (Hou and Yao, 2019). Nevertheless, when rural labor transfer reaches its saturation point or exceeds optimal thresholds, the agricultural production system stabilizes at a new equilibrium. Within this context, the marginal returns from chemical input-intensive production structures exhibit diminishing trends, while environmental degradation intensifies, creating incentives for behavioral change among agricultural producers. In addition, the emergence of green production technologies and agricultural socialized service organizations has fundamentally altered traditional production paradigms. These developments have provided viable alternatives to chemical input-dependent production methods. Therefore, under the dual influence of national policies promoting chemical input reduction and the availability of sustainable alternatives, agricultural producers demonstrate increased willingness to adopt socialized agricultural services and green production technologies. This behavioral shift, motivated by rational economic considerations, facilitates the transition toward sustainable agricultural practices, thereby creating opportunities for effective management of ANPP. Under the influence of these dynamic factors, the marginal impact of rural labor transfer on ANPP demonstrates significant variation across different stages and scales of implementation. Hence, Hypothesis 4 (H4) is proposed.

> *H4:* The effect of rural labor transfer on agricultural non-point source pollution has nonlinear characteristics.

Building upon the aforementioned theoretical analysis and the formulation of relevant hypotheses, this study establishes a comprehensive conceptual framework that examines the interrelationships among rural labor transfer, non-farm income, agricultural socialized services, and ANPP, as illustrated in Figure 1.

## 3 Materials and methods

### 3.1 Model selection

To investigate the relationship between rural labor transfer and ANPP, this study employs a series of econometric models, including a two-way fixed effects model, a mediating effect model, a moderating effect model, and a threshold model. The two-way fixed effects model controls for unobserved regional heterogeneity and time-varying trends in panel data, accurately identifying the causal impact of rural labor transfer on ANPP by mitigating endogeneity from omitted variables. The mediating effect model uncovers the transmission pathways through which rural labor transfer influences ANPP, enhancing theoretical clarity on causal mechanisms. The moderating effect model examines the role of agricultural socialized services, identifying how agricultural socialized services change the magnitude and direction of the relationship between non-farm income and ANPP. The threshold model detects nonlinear dynamics, estimating critical points where rural labor transfer's impact on ANPP shifts abruptly. Collectively, these models integrate causal inference, mechanism analysis, contextual variation, and nonlinearity, providing a comprehensive framework to decode the multifaceted link between labor mobility and ANPP. The specifications of these models are detailed as follows.

#### 3.1.1 Benchmark regression model

To minimize endogenous interference as much as possible, this paper adopts a dual fixed effect model of provincial fixation and time fixation to test the relationship between rural labor transfer and ANPP.

$$\ln ANPP_{it} = \alpha_0 + \alpha_1 \ln rlt_{it} + \alpha_2 Control_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{1}$$

Herein, $ANPP_{it}$ is the ANPP in region $i$ at time $t$, $rlt_{it}$ is the number of rural labor transfer in region $i$ at time $t$, and $Control_{it}$ is the set of control variables. $\mu_i$ is the regional fixed effect, $\tau_t$ is the time fixed effect, $\varepsilon_{it}$ is the random disturbance term. $\alpha_1$ represents the overall impact of rural labor transfer on ANPP.

#### 3.1.2 Mediating effect model

Referring to Baron and Kenny (1986), this research develops a mediating effect model to test whether *nfin* has a mediating role in the effects of rural labor transfer on ANPP.

$$nfin_{it} = \beta_0 + \beta_1 \ln rlt_{it} + \beta_2 Control_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{2}$$

$$\ln ANPP_{it} = \gamma_0 + \gamma_1 \ln rlt_{it} + \gamma_2 nfin_{it} + \gamma_3 Control_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{3}$$

Herein, $\gamma_1$ represents the direct impact of rural labor transfer on ANPP, $\beta_1 \times \gamma_2$ is the mediating effect which is equal to the indirect effect, $nfin_{it}$ is the non-farm income, and the other variables are as described above.

#### 3.1.3 Moderating effect model

To examine whether agricultural socialized services have a moderating effect on non-farm income and ANPP, a moderating effect model is established as follows.

$$\begin{aligned} \ln ANPP_{it} &= \delta_0 + \delta_1 \ln rlt_{it} + \delta_2 nfin_{it} + \delta_3 \ln assv_{it} \\ &+ \delta_4 nfin_{it} \times \ln assv_{it} + \delta_5 Control_{it} + \mu_i + \tau_t + \varepsilon_{it} \end{aligned} \tag{4}$$

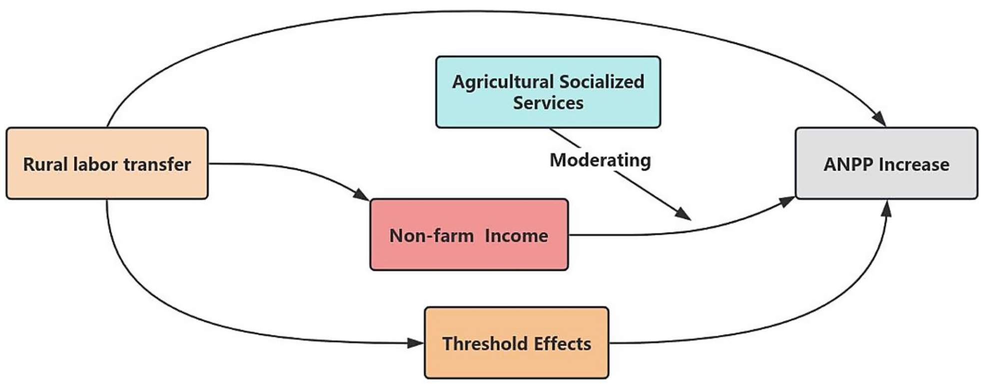


FIGURE 1
Conceptual framework.

Herein, $assv_{it}$ is the output value of agricultural socialized services in region $i$ at time $t$, $nfin_{it} \times \ln assv_{it}$ is the interaction between non-farm income and the value of agricultural socialized services which is used to investigate the moderating effect. Other variables are as described above.

### 3.1.4 Threshold model

With reference to the threshold model theory for panel data from Hansen (1999), rural labor transfer is used as the threshold variable to investigate the nonlinear characteristics of the impact of rural labor transfer on ANPP.

$$\ln ANPP_{it} = \lambda_0 + \lambda_1 \ln rlt_{it} \times I\left(\ln rlt_{it} \le q_1\right) + \lambda_2 \ln rlt_{it} \times I\left(\ln rlt_{it} > q_n\right) + \lambda_3 Control_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (5)$$

Herein, $q$ is the threshold value, and the indicative function indicates that when the threshold variable satisfies the conditions in parentheses, the value is 1, otherwise it is 0. The other variables are as described above.

## 3.2 Variable selection

### 3.2.1 Dependent variable

ANPP (*ANPP*). Fertilizers and pesticides are important input sources of ANPP (Wang et al., 2022; Jiang et al., 2021). With referring to Shao and Li (2020) ANPP is characterized by the application intensity of fertilizers and pesticides in each province to represent the total application intensity of fertilizers and pesticides per hectare of crop sown area. The formula is as follows:

$$ANPP_{it} = \frac{Totalfert_{it} + Totalpest_{it}}{Crop_{it}} \quad (6)$$

Herein, $Totalfert_{it}$ is the conversion amount of chemical fertilizer application, $Totalpest_{it}$ is the amount of pesticide application, and $Crop_{it}$ is the sown area of crops in the Equation (6).

### 3.2.2 Independent variable

Rural labor transfer (*rlt*). This paper characterizes rural labor transfer using the rural migrant labor force, quantified as the total number of year-round migrant laborers and seasonal migrant laborers. Specifically, the number of year-round migrant laborers is calculated as the sum of three categories: laborers working outside their township but within the county, those working outside the county but within the province, and those working outside the province.

### 3.2.3 Mediating variable

*Non-farm income* (*nfin*). The income obtained from the transfer of rural labor force is an important part of the livelihood capital of farmers' families. The more wage income obtained, the higher the enthusiasm of farmers to increase capital investment in agricultural production (Shao et al., 2021). Therefore, the proportion of migrant workers' wage income to rural residents' disposable income is used to characterize the level of farmers' non-farm income.

### 3.2.4 Moderating variable

Agricultural socialized services (*assv*). The level of agricultural socialized services is defined in this study using the output values of agriculture, forestry, animal husbandry, and fishing services. The term "agriculture, forestry, animal husbandry, and fishery service industry "refers to all forms of service activities that support the production of agriculture, forestry, animal husbandry, and fishery, excluding all forms of science, technology, and professional and technical service activities. But it is conceptually and substantively similar to the agricultural productive service industry and can be used to gauge the level of development of agriculture (Zhang and Guo, 2021). In addition, the output value of agriculture, forestry, animal husbandry and fishery service industry is converted into a comparable variable with 2005 as the base period to make the data vertically comparable.

### 3.2.5 Control variables

The control variables are mainly divided into economic variables, population variables and environmental variables. Among them, economic variables include the following: (1) Per capita GDP (*pgdp*), measured by total domestic GDP to total population. Generally, the more developed the economy is, the more people attach importance to the ecological environment, and the less the possibility of ANPP. (2) Agricultural technological innovation (*ati*), measured by the number of authorized patents of agricultural enterprises (the sum of the number of authorized patents of invention, utility and appearance). Technological progress is conducive to increasing agricultural production efficiency and improving agricultural production methods, thus promoting the management of ANPP. (3) Financial expenditure on agriculture (*finp*), expressed as the proportion of agricultural, forestry and water affairs expenditure in the total financial expenditure. The influence of agricultural fiscal expenditure on agricultural pollution is uncertain. On the one hand, agricultural fiscal expenditure helps to reduce the emission of agricultural pollutants; On the other hand, agriculture-related expenditures such as agricultural subsidies can stimulate farmers to increase input of factors such as fertilizers and pesticides, which may exacerbate ANPP. (4) Grain yield per unit area (*grain*), which reflects the production intensity of grain. Higher grain yield per unit area may be related to the use of more agricultural inputs, thus affecting ANPP. (5) Multiple cropping index (*cropind*), means that the sown area of crops on arable land to the area of arable land during the whole year. Moderate replanting on existing arable land can optimize the crop planting structure, and drive the optimal adjustment of the structure of agricultural input factors, thus alleviating ANPP. Population variables include the following: (1) Rural population aging (*aging*), expressed using the rural elderly dependency ratio. With the deepening of the rural population aging, more farmers are encouraged to adopt green production technology for agricultural production, which may inhibit ANPP. (2) Urbanization rate (*ubr*), meaning that the urban population is divided by the total population. In areas with high urbanization level, the population density is more concentrated, resulting in crowding out agricultural resources, producing a large number of production and domestic pollution sources, and aggravating the damage to the ecological

TABLE 1 Descriptive statistics analysis of variables.

| Variable classification | Variables | Mean | SD | Min | Max | Obs |
|---|---|---|---|---|---|---|
| Dependent variable | ln *ANPP* | 5.883 | 0.427 | 4.407 | 7.305 | 540 |
| Independent variable | ln *rlt* | 6.107 | 1.188 | 2.674 | 7.951 | 540 |
| Mediating variable | *nfin* | 0.378 | 0.149 | 0.075 | 0.763 | 540 |
| Moderating variable | ln *assv* | 4.538 | 1.331 | 1.088 | 7.126 | 540 |
| Interaction | *nfin* × ln *assv* | −0.037 | 0.239 | −1.094 | 0.507 | 540 |
| Control variables | ln *pgdp* | 10.584 | 0.694 | 8.560 | 12.207 | 540 |
| | ln *ati* | 7.810 | 1.273 | 4.145 | 10.467 | 540 |
| | *finp* | 0.106 | 0.034 | 0.021 | 0.204 | 540 |
| | ln *grain* | 8.554 | 0.204 | 8.021 | 9.008 | 540 |
| | *cropind* | 1.287 | 0.399 | 0.418 | 2.503 | 540 |
| | *aging* | 0.175 | 0.072 | 0.071 | 0.469 | 540 |
| | ln *ed* | 2.122 | 0.144 | 1.639 | 2.540 | 540 |
| | *ubr* | 0.571 | 0.141 | 0.269 | 0.896 | 540 |
| | *precip* | 0.944 | 0.536 | 0.061 | 2.503 | 540 |
| | *temp* | 13.110 | 6.103 | −2.068 | 26.289 | 540 |
| | ln *drainage* | 5.614 | 1.574 | 0.000 | 8.454 | 540 |

environment. (3) Average level of education of rural residents (*ed* ). The greater the education level, the more likely they are to employ environmentally friendly methods of production for agricultural activities to reduce ANPP. Environmental variables include the following: (1) Precipitation (*precip*), and temperature (*temp*), which used to reflect the impact of climate change on ANPP. (2) Drainage methods (*drainage*), expressed as village drainage pipe laying length. Different agricultural drainage methods may have different impacts on ANPP. Installing drainage pipes is beneficial for concentrating and treating domestic and agricultural wastewater, which may help alleviate ANPP.

## 3.3 Data sources

Panel data of 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2005 to 2022 are selected as research samples. The data is collected from 2006—2023 National Statistical Yearbook, China Rural Statistical Yearbook, National Rural Economic Statistics, China Rural Management Statistical Annual Report, China Rural Policy and Reform Statistical Annual Report, China Population and Employment Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Water Statistical Yearbook, and provincial statistical yearbooks. A small number of missing data are filled by linear interpolation method. Logarithms are taken for ANPP, rural labor transfer, output value of agricultural socialized services, per capita GDP, the average education level of rural residents and drainage methods to reduce data volatility and address issues like heteroscedasticity. Descriptive statistics of each variable are shown in Table 1.

# 4 Empirical results analysis

## 4.1 Effect of rural labor transfer on ANPP

Before using Equation (1) for benchmark regression, the applicability of the model is tested. The random effects model is disregarded by Hausman's test (chi2(11) = 15.29, Prob > chi2 = 0.0001), indicating that a fixed effects model is preferable for estimation. Robust standard errors are employed for estimate in all subsequent regression models. Furthermore, unit root tests are performed using Levin Lin Chu (LLC) test, Bruiting test, Im Peraran Shin (IPS) test, and Augmented Dickey-Fuller (ADF) test.[1] All variables pass at least the above three panel unit root tests, suggesting that the selected variables are stationary.

Table 2 reports the empirical results on the impact of rural labor transfer on ANPP. Model (1) demonstrates the regression results without control variables, revealing a statistically significant coefficient of 0.212 at the 1% level, indicating a positive association between rural labor transfer and ANPP. The inclusion of control variables in Model (2) yields a slightly attenuated yet statistically robust coefficient of 0.207, maintaining significance at the 1% level. This consistent positive relationship suggests that rural labor transfer contributes to the exacerbation of ANPP, further validating the research findings of (Luan and Han, 2021). To ensure the robustness of our findings, Model (3) incorporates Bootstrap robust standard errors to address potential estimation biases. The results confirm the stability of both

1 Detailed results are not disclosed due to limited space.

TABLE 2 Influence of rural labor transfer on ANPP.

| Variables | (1) | (2) | (3) |
|---|---|---|---|
| | ln *ANPP* | ln *ANPP* | ln *ANPP* |
| ln *rlt* | 0.212*** | 0.207*** | 0.207*** |
| | (0.046) | (0.045) | (0.048) |
| ln *pgdp* | | 0.016 | 0.016 |
| | | (0.016) | (0.017) |
| ln *ati* | | 0.032*** | 0.032*** |
| | | (0.012) | (0.012) |
| *finp* | | 0.788** | 0.788** |
| | | (0.313) | (0.321) |
| ln *grain* | | 0.377*** | 0.377*** |
| | | (0.090) | (0.096) |
| *cropind* | | −0.099*** | −0.099*** |
| | | (0.035) | (0.037) |
| *aging* | | 0.085 | 0.085 |
| | | (0.235) | (0.240) |
| *ubr* | | −0.167 | −0.167 |
| | | (0.112) | (0.116) |
| ln *ed* | | −0.161 | −0.161 |
| | | (0.160) | (0.169) |
| *precip* | | 0.012 | 0.012 |
| | | (0.020) | (0.021) |
| *temp* | | −0.015 | −0.015 |
| | | (0.012) | (0.014) |
| ln *drainage* | | −0.000 | −0.000 |
| | | (0.010) | (0.010) |
| *Constant* | 4.591*** | 1.629 | 2.728*** |
| | (0.284) | (1.007) | (0.967) |
| $\mu_i$ | No | Yes | Yes |
| $\tau_t$ | No | Yes | Yes |
| *N* | 540 | 540 | 540 |
| *Adj.* $R^2$ | 0.947 | 0.956 | 0.956 |
| *F* | 20.735 | 8.828 | |

Standard error are reported in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the coefficient magnitude and direction, thereby reinforcing the validity of our initial findings. Consequently, we conclude that rural labor transfer significantly exacerbates ANPP, generating negative externalities in agricultural production and substantiating H1.

The analysis of control variables in Model (2) reveals several noteworthy patterns. It is evident from the table that among the economic variables, agricultural technological innovation, financial expenditure on agriculture, and the level of grain yield per unit area exert a significant positive impact on ANPP. This could be attributed to the fact that while agricultural technological progress enhances production efficiency, it has not yet fully achieved a green transformation in the short term. Meanwhile, the utilization of fiscal funds for agricultural support may indirectly stimulate an increase in inputs such as chemical fertilizers and pesticides. Additionally, the improvement in grain yield per unit area is often accompanied by greater investment in agricultural production factors, thereby exacerbating ANPP. In contrast, the multiple cropping index has a significant negative impact on ANPP. This is because appropriate multiple cropping optimizes the crop planting structure and drives the rational adjustment of the structure of agricultural input factors, thereby alleviating ANPP.

Population variables, which include rural population aging, urbanization rate, and the average educational level of rural residents, are used to capture the impact of changes in population structure and quality on ANPP. In the benchmark regression, none of the aforementioned population control variables showed significant effects. This may be due to the fact that, at the current stage, the promoting effect of rural population aging on the adoption of green production technologies, the resource crowding-out and pollution-increasing effects brought by the urbanization rate, and the facilitating effect of improved educational levels of rural residents on environmentally friendly production methods offset each other.

Environmental variables, including precipitation, temperature, and drainage methods, reflect the impact of natural conditions and infrastructure on ANPP. These environmental control variables in the table also did not exhibit significant effects. Although, in theory, drainage methods can alleviate ANPP through centralized treatment of domestic and agricultural wastewater, and climatic factors such as precipitation and temperature may affect the diffusion and occurrence of ANPP through natural processes, the role of these factors in this regression model has not reached a statistically significant level.

## 4.2 Mediating role of non-farm income

To test whether rural labor transfer act indirectly on ANPP through farmers' non-farm income, the mediating effect of non-farm income is empirically estimated using Equations (2) and (3). Table 3 reports the results of the mediating effect of non-farm income. Model (1) reflects the overall effect of rural labor transfer on ANPP. Model (2) reflects the impact of rural labor transfer on non-farm income. The transfer of rural labor force changes by 1 percentage point, and non-farm income can significantly increase by 0.064 percentage points, indicating the existence of mediating effect. Model (3) reflects the impact of non-farm income on ANPP after controlling for the direct effect of rural labor transfer on ANPP. And it is found that the coefficients of rural labor transfer and non-farm income on ANPP are 0.184 and 0.368, respectively, and that pass the test at the 1% significance level, indicating that the indirect effect is obvious. Based on the above results, it can be seen that the promoting effect of rural labor transfer on ANPP can follow the path of "rural labor transfer → non-farm income →ANPP," that is, non-farm income plays a mediating role in the impact of rural labor force transfer on ANPP, thereby verifying H2. It also supports the viewpoints of Wu and Liu (2017) and Shao and Li (2020). The test of Sobel and Bootstrap are used to examine the mediating effect to further confirm the reliability of the findings. As shown in Table 3, the Z-value of Sobel test is 2.686, which is significant at the 1% level, indicating that non-farm income acts as a mediator. The findings of the Bootstrap test of the mediation

TABLE 3 Mediating effects of non-farm income and moderating effects of agricultural socialized services.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln *ANPP* | ln *ANPP* | *nfin* | ln *ANPP* |
| ln *rlt* | 0.207*** | 0.064*** | 0.184*** | 0.159*** |
| | (0.045) | (0.018) | (0.043) | (0.040) |
| *nfin* | | | 0.368*** | 0.317*** |
| | | | (0.090) | (0.082) |
| ln *assv* | | | | 0.005 |
| | | | | (0.022) |
| *nfin* × ln *assv* | | | | −0.230*** |
| | | | | (0.055) |
| *Control variables* | Yes | Yes | Yes | Yes |
| $\mu_i$ | Yes | Yes | Yes | Yes |
| $\tau_t$ | Yes | Yes | Yes | Yes |
| *Constant* | 1.629 | 0.240 | 1.541 | 2.245*** |
| | (1.007) | (0.326) | (0.974) | (0.857) |
| *Sobel Test* | 2.686*** | | | |
| *Goodman-1* | 2.641*** | | | |
| *Goodman-2* | 2.733*** | | | |
| *N* | 540 | 540 | 540 | 540 |
| *Adj. $R^2$* | 0.956 | 0.922 | 0.957 | 0.960 |
| *F* | 8.828 | 14.861 | 9.237 | 10.889 |

Standard errors are reported in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

effect after 500 iterations of self-sampling are displayed in Table 4. It demonstrates that both direct and indirect impact coefficients are statistically significant in the positive direction, and the test for the mediating effect does not contain a value of 0 within the 95% confidence interval, effectively also suggesting the presence of the mediating effect (Hayes and Preacher, 2014). It is calculated that the mediating effect of non-farm income is 11.11% as the direct effect coefficient is 0.184 and the indirect effect coefficient is 0.023.

## 4.3 Moderating role of agricultural socialized services

Model (4) in Table 3 presents the moderating effect of agricultural socialized services. To mitigate potential multicollinearity, the output value of agricultural socialized services and non-farm income were standardized before regression analysis using Equation (4). Subsequently, interaction terms were constructed and incorporated into Model (4). The results show that the regression coefficient of agricultural socialized services is 0.005, which does not reach statistical significance, indicating that its direct impact on ANPP when acting alone is not obvious. However, the coefficient of its interaction term with non-farm income is −0.230, and it is significant at the 1% level, indicating that the interaction has a significant impact on ANPP. Meanwhile, the coefficient of non-farm income dropped from 0.368 to 0.317 (−13.86%). This change indicates that agricultural socialized services have weakened the mediating role of non-farm income in the relationship between rural labor transfer and ANPP. Further analysis through the marginal effect equation reveals that when the output value of agricultural socialized services reaches 396.799 million yuan, the "pollution-increasing effect" of non-farm income will reverse. It is that before this critical point, non-farm income may drive the intensification of ANPP. When the output value of agricultural socialized services exceeds this figure, the role of non-farm income on ANPP will shift from "promotion" to "inhibition." Based on the data in Table 1, the minimum value of the output value of agricultural socialized services is 1.087 and the maximum value is 7.126. This indicates that in most provinces of China, agricultural socialized services have reached a level that can reverse the pollution-increasing effect of non-farm income, and their pollution reduction role has been actually demonstrated, thereby validating H3.

## 4.4 Robustness tests

In the benchmark regression estimation, there may be errors when choosing method and variable leading to biased results, and to ensure the reliability of the benchmark regression results, the robustness tests are conducted as follows.

### 4.4.1 Replace independent variable

The proportion of rural migrant workers is chosen as the alternative variable of rural labor transfer, that is, the proportion of rural migrant workers = the total number of rural migrant workers/rural labor force * 100%. Meanwhile, the sum of the employment number of the secondary and tertiary industries is also used as the replacement variable of rural labor transfer (Zhao and Jing, 2019; Jiang et al., 2023). The model (1)–(2) in Table 5 reports the robustness test results, the coefficient of rural labor transfer passes the test at 1, 5, and 10% significance level respectively, and the direction is consistent with the model (2) in Table 2, indicating that the conclusion is robust.

### 4.4.2 Extended the samples

Considering the key variables for 2023 are complete, the research sample is extended to 2023 by addressing missing data in the control variables through linear interpolation to further validates the robustness of the baseline regression results. As demonstrated in Model (3) of Table 5, the effect of rural labor transfer on ANPP remains significantly positive, with the coefficient value showing a slight increase compared to the original baseline regression model. This finding reinforces the robustness of the positive relationship between rural labor transfer and ANPP.

### 4.4.3 Select the sub-samples

Given the unique policy and economic development status of Beijing, Tianjin, Shanghai, and Chongqing within China, subsamples corresponding to these four municipalities were excluded to minimize potential estimation biases. The robustness test results, as shown in Model (4) of Table 5, demonstrate that the significance and direction of the coefficients for rural labor transfer remain highly consistent with those in Model (2) of Table 2.

TABLE 4 Results of Bootstrap test.

| Effect types | Coefficients | Bootstrap standard errors | Z-statistics | $P > \|Z\|$ | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| Direct effect | 0.184 | 0.044 | 4.21 | 0.009 | 0.098 | 0.269 |
| Indirect effect | 0.023 | 0.009 | 2.60 | 0.000 | 0.006 | 0.041 |

TABLE 5 Robustness test and endogeneity test results.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *rlt* | ln *ANPP* |
| ln *rlt* | 0.007*** | 0.163** | 0.218*** | 0.291*** | 0.181*** | 0.167*** | | 0.230*** |
| | (0.002) | (0.072) | (0.043) | (0.075) | (0.051) | (0.053) | | (0.060) |
| *IV* | | | | | | | 0.788*** | |
| | | | | | | | (0.102) | |
| K-P rk LM statistic | | | | | | | | 29.762<0.000> |
| Cragg-Donald Wald F statistic | | | | | | | | 778.556<16.38> |
| Hansen J statistic | | | | | | | | 0.000 |
| *Control variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $\mu_i$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $\tau_t$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 2.735*** | 2.155* | 1.226 | −0.832 | 2.030** | 2.182** | −0.099 | 2.845*** |
| | (0.912) | (1.112) | (0.937) | (1.165) | (1.030) | (1.004) | (0.046) | (0.907) |
| *N* | 540 | 540 | 570 | 468 | 510 | 510 | 510 | 510 |
| *Adj. $R^2$* | 0.955 | 0.954 | 0.946 | 0.968 | 0.957 | 0.958 | / | 0.962 |
| *F* | 6.560 | 7.143 | 7.575 | 9.436 | 6.863 | 7.607 | 59.960 | 525.34 |

Standard errors are reported in parentheses, *, ** and *** represent significance levels of 10%, 5%, and 1% respectively. *p*-values in Kleibergen-Paap rk LM statistic parentheses, Cragg-Donald Wald F statistic in parentheses is the critical value corresponding to 10% maximal IV size in Stock-Yogo weak ID test.

## 4.5 Endogeneity test

The potential issue of endogeneity arising from mutual causality may exist in the relationship between rural labor transfer and ANPP. To address this concern and ensure the unbiased nature of our model estimates presented in Table 5, two methodological approaches are employed to examine the endogeneity of model.

Firstly, drawing upon the methodological approach established by Ashley et al. (2018), we implement a temporal adjustment by replacing the current values with the independent variable lagged by one period and the dependent variable advanced by one period to mitigate potential endogeneity concerns in models (5) and (6). Secondly, following the methodological approach of Lee and Wang (2022), the lagged variable of rural labor transfer is selected as an instrumental variable. The paper subsequently employs the Two-Stage Least Squares method (IV_2SLS) to estimate the effect of rural labor transfer on ANPP. The robustness of the instrumental variable approach is supported by several diagnostic tests as follows. The first-stage F statistic ($F = 29.762$) in model (7) exceeds the conventional threshold of 10, indicating a statistically strong correlation between the endogenous variables and the instrumental variables. Furthermore, as evidenced in model (8), the Cragg-Donald Wald F statistic (778.556) surpasses the critical value at the 10% significance level, thereby dismissing concerns regarding weak instrumental variables. Additionally, the Kleibergen-Paap rk LM statistics consistently reject the null hypothesis of underidentification at the 1% significance level, while the Hansen J statistic indicates the absence of over-identification issues, collectively confirming the appropriateness of the selected instrumental variable. The regression results from models (5) through (8) in Table 5 demonstrate that the significance level and directional impact of rural labor transfer on ANPP remain consistent with the findings from model (2). This consistency persists even after accounting for potential endogeneity, suggesting that rural labor transfer continues to exert a positive influence on ANPP when endogeneity considerations are incorporated into the analysis.

## 4.6 Heterogeneity analysis

### 4.6.1 Heterogeneity analysis of impacts of different types of rural labor transfer on ANPP

To further investigate the differential impacts of various types of rural labor transfer on ANPP, we disaggregate the total number of rural labor transfer into two distinct categories: year-round migrant labor force ($\ln rlt1$) and seasonal migrant labor force ($\ln rlt2$). This classification enables us to examine the distinct effects of long-term versus short-term rural labor transfer on ANPP. Additionally, we further categorize the year-round migrant labor force into three subgroups based on migration distance: local transfer (within the county but outside the township, $\ln rlt3$), intra-provincial transfer (outside the county but within the province, $\ln rlt4$), and inter-provincial transfer (outside the province, $\ln rlt5$). This finer classification allows us to analyze the differential impacts of local, intra-provincial, and inter-provincial rural labor transfer on ANPP.

The regression results presented in Table 6 reveal significant differences in the environmental impacts of these labor transfer patterns. Models (1) and (2) report the regression coefficients for year-round and seasonal migrant labor forces, respectively. The analysis indicates that year-round rural labor transfer exerts a significantly greater impact on ANPP compared to seasonal transfer. This differential impact may be attributed to the more stable non- farm income streams available to year-round migrant workers, which enhance their livelihood capital and enable increased investment in agricultural inputs such as pesticides and fertilizers to compensate for reduced agricultural labor availability. In contrast, seasonal migrant workers typically return to their agricultural activities during peak farming seasons, thereby mitigating labor shortages. Moreover, their periodic exposure to external knowledge and technologies through migration experiences facilitates the adoption of improved agricultural practices, resulting in a relatively smaller environmental impact.

TABLE 6 Heterogeneity test of different types of rural labor transfer affecting ANPP.

| Variables | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *ANPP* |
| $\ln rlt1$ | 0.187*** | | | | |
| | (0.049) | | | | |
| $\ln rlt2$ | | 0.037*** | | | |
| | | (0.014) | | | |
| $\ln rlt3$ | | | 0.075 | | |
| | | | (0.048) | | |
| $\ln rlt4$ | | | | 0.131*** | |
| | | | | (0.042) | |
| $\ln rlt5$ | | | | | 0.093*** |
| | | | | | (0.025) |
| *Control variables* | Yes | Yes | Yes | Yes | Yes |
| $\mu_i$ | Yes | Yes | Yes | Yes | Yes |
| $\tau_t$ | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 2.185** | 2.876*** | 2.796*** | 2.385** | 2.915*** |
| | (0.960) | (0.901) | (0.953) | (0.950) | (0.879) |
| *N* | 540 | 540 | 540 | 540 | 540 |
| *Adj. $R^2$* | 0.956 | 0.954 | 0.954 | 0.954 | 0.955 |
| *F* | 7.508 | 6.815 | 6.026 | 7.371 | 7.890 |

Standard errors are reported in parentheses," *, ** and *** represent significance levels of 10%, 5%, and 1% respectively.

The regression results from Models (3) to (6) indicate significant differences in the impact of rural labor migration across varying distances on ANPP. Specifically, the effect of local transfer is insignificant. This is primarily because locally migrated laborers typically reside within a geographically proximate range, enabling them to balance non-farm employment with continued involvement in agricultural production. Their higher dependence on agriculture, coupled with low migration costs that facilitate flexible commuting between urban and rural areas, means they neither completely abandon farming nor resort to excessive inputs like fertilizers and pesticides due to income insufficiency. Consequently, their impact on ANPP remains minimal and statistically insignificant. In contrast, intra-provincial transfer exhibits a significant positive coefficient of 0.131. Labor transfer within the province typically enter secondary or tertiary industries such as manufacturing, construction, or services, but often earn wages lower than those transfer across provinces. This results in non-farm income insufficient to fully replace agricultural earnings. As household income remains partially reliant on agriculture, farmers may increase inputs like fertilizers and pesticides to boost per-unit yield, compensating for the shortfall in non-farm income and thereby exacerbating ANPP. Inter-provincial transfer also shows a significant positive coefficient (0.093), though its effect is weaker than that of intra-provincial transfer. This attenuation likely stems from the fact that intra-provincial transfer generally enter higher-paying sectors in more economically developed regions. Their significantly higher wages enable them to substantially increase total household income through remittances. The resultant higher non-farm income reduces household dependence on agriculture. Some farmers may consequently reduce agricultural production or even abandon land, partially mitigating ANPP. However, due to the higher costs associated with cross-provincial migration, some households may opt to transfer their land to other farmers for consolidated operation. These large-scale operators might then adopt more intensive agricultural practices, leading to a residual increase in pollution. Nevertheless, the overall positive impact on ANPP remains smaller than that observed for intra-provincial transfer.

### 4.6.2 Heterogeneity analysis of rural labor transfer affecting ANPP in different regions

Due to the vast regional differences in rural labor transfer throughout China, we posit that its effect on ANPP is likely to be highly regional. Accordingly, to capture this geographical heterogeneity, we grouped the sample according to the existing regional classification of eastern, northeastern, central, and western China. The regression results presented in Table 7 reveal significant regional variations in the impact coefficients of rural labor transfer on ANPP. Specifically, the coefficients for the eastern, central, and western regions are 0.094, 0.366, and 0.288, respectively, all statistically significant at the 5% level. In contrast, the northeastern region exhibits a negative but statistically insignificant coefficient.

A comparative analysis of these coefficients indicates that the central region demonstrates the most pronounced impact (0.366), a phenomenon that can be attributed to its unique agricultural characteristics and developmental stage. As China's primary grain production base, the central region maintains a high level of agricultural intensification. The substantial outflow of rural labor has exacerbated agricultural labor shortages, compelling farmers to increase their reliance on chemical inputs such as fertilizers and pesticides to sustain

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TABLE 7 Heterogeneity test of rural labor transfer affecting ANPP in different regions.

| Variables | Eastern region | Northeastern region | Central region | Western region |
|---|---|---|---|---|
| | ln *ANPP* | ln *ANPP* | ln *ANPP* | ln *ANPP* |
| ln *rlt* | 0.094** | −0.276 | 0.366*** | 0.288*** |
| | (0.043) | (0.479) | (0.112) | (0.091) |
| *Control variables* | Yes | Yes | Yes | Yes |
| $\mu_i$ | Yes | Yes | Yes | Yes |
| $\tau_t$ | Yes | Yes | Yes | Yes |
| *Constant* | 8.845*** | 12.948*** | 1.480 | −0.144 |
| | (1.505) | (3.132) | (1.295) | (1.495) |
| *N* | 180 | 54 | 108 | 198 |
| *Adj. R*$^2$ | 0.911 | 0.993 | 0.973 | 0.977 |
| *F* | 17.561 | 8.395 | 15.331 | 7.606 |

Standard errors are reported in parentheses, *, ** and *** represent significance levels of 10%, 5%, and 1% respectively.

productivity. This intensified chemical usage, coupled with the region's relatively limited adoption of advanced agricultural technologies and environmental protection measures, has significantly amplified the positive correlation between rural labor transfer and ANPP. The western region exhibits a moderate impact coefficient (0.288), which may reflect its distinctive geographical and economic conditions. The region's complex topography and fragile ecological environment naturally limit the scale of agricultural production. The reduction in agricultural labor due to rural labor migration has likely prompted farmers to compensate through increased chemical inputs, thereby exacerbating non-point source pollution. Furthermore, the region's underdeveloped environmental infrastructure and limited pollution control capacity have further magnified the environmental consequences of rural labor transfer. In contrast, the eastern region demonstrates the lowest impact coefficient (0.094), a finding that aligns with its advanced economic development and higher level of agricultural modernization. The widespread implementation of precision agricultural technologies in this region has encouraged the adoption of more efficient and environmentally sustainable farming practices, such as precision fertilization and integrated pest management. These technological advancements, combined with the region's stringent environmental regulations and robust pollution control measures, have substantially mitigated the potential negative environmental impacts of rural labor transfer. The northeastern region presents an intriguing case, with a negative but statistically insignificant regression coefficient. This pattern may be explained by the region's distinctive agricultural structure and labor transfer characteristics. As a crucial commodity grain base in China, the northeastern region boasts a high level of agricultural mechanization, which has reduced the production impacts of labor migration. Moreover, the prevalence of large-scale agricultural operations in this region has facilitated the adoption of mechanized practices and scientific management approaches, thereby decreasing reliance on chemical inputs. While these factors suggest a potential inhibitory effect of rural labor transfer on ANPP, this relationship has not yet achieved statistical significance in our analysis.

### 4.7 Threshold effects

To examine the threshold effect of rural labor transfer, this section employs Equation (5) for empirical testing." before the sentence" As evidenced by the results presented in Table 8, the corresponding *F*-value achieves statistical significance at the 5% level, confirming the existence of a single threshold effect in the relationship between rural labor transfer and ANPP, with a threshold value of 3.967 ($q = 3.967$). The threshold regression results, as detailed in Table 9, demonstrate distinct patterns of influence across different scales of rural labor transfer. When the logarithmic value of rural labor transfer remains below or equal to the threshold of 3.967, the estimated coefficient for its impact on ANPP is 0.199, significant at the 1% level. Conversely, when the logarithmic value exceeds this threshold, the estimated coefficient decreases to 0.141, while maintaining statistical significance at the 1% level. These findings suggest a non-linear relationship between rural labor transfer and ANPP, wherein the marginal effect of rural labor transfer on pollution intensity diminishes as the scale of transfer increases beyond the identified threshold. This empirical evidence provides robust support for H4, indicating that while rural labor transfer generally exacerbates ANPP, its promoting effect attenuates as the scale of transfer expands beyond a critical point.

## 5 Discussion and limitations

China confronts dual challenges of massive rural labor migration and escalating ANPP, as labor shortages drive intensive pesticide/fertilizer use, exacerbating environmental degradation (Xie and Lu, 2017; Shi et al., 2016). While prior studies, such as Shao et al. (2021), established a linear link between labor transfer and pollution by showing household migration increases pollution probability, and Guo et al. (2022) demonstrated that labor-driven wage hikes boost pesticide consumption, these works overlooked critical mechanisms. In contrast, this study advances the field by:

(1) Unveiling non-linear dynamics: Through a threshold model, we identify a critical inflection point (log value 3.967) where rural labor transfer's marginal impact on ANPP declines from 0.199 to 0.141, challenging the linear assumptions in conventional research (Guo et al., 2022; Zhang et al., 2020; Shi et al., 2016). This aligns with the "pollution transition" theory in developing economies, where labor outflow initially intensifies pollution but triggers adaptive behaviors at higher scales.
(2) Mediating-moderating mechanism integration: Unlike studies focusing on single pathways (Shou et al., 2019; Gallardo and Sauer, 2018), we reveal non-farm income acts as a key mediator (11.11% mediating effect), while agricultural socialized services moderate this relationship—reducing 13.86% of pollution caused by the increase in non-agricultural income. This integrates income-driven pollution amplification with service-driven mitigation, a framework absent in prior work (Shou et al., 2019; Ge and Wu, 2023; Yan et al., 2021; Liu et al., 2022).
(3) Regional heterogeneity quantification: Our analysis distinguishes impacts across rural labor transfer types and regions, whereas most studies overlook spatial disparities (Das

TABLE 8 Threshold effects test.

| Threshold variable | Models | Fstat | Prob | Boostrap times | Critical value | | | Threshold estimator |
|---|---|---|---|---|---|---|---|---|
| | | | | | 10% | 5% | 1% | |
| ln *rlt* | Single threshold | 66.27** | 0.020 | 500 | 48.310 | 56.421 | 73.967 | 3.967 |
| | Double threshold | 22.90 | 0.738 | 500 | 42.747 | 48.213 | 63.293 | 5.497 |
| | Triple threshold | 16.40 | 0.730 | 500 | 48.405 | 56.160 | 74.967 | 6.809 |

*, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

TABLE 9 Nonlinear characteristics of rural labor transfer affecting ANPP.

| Variable | ln *ANPP* |
|---|---|
| $\ln rlt(\ln rlt \leq 3.967)$ | 0.199***(0.034) |
| $\ln rlt(\ln rlt > 3.967)$ | 0.141***(0.031) |
| *Control variables* | Yes |
| *Threshold value* | 3.967 |
| *N* | 540 |
| $R^2$ | 0.447 |

Standard errors are reported in parentheses," *, **, and *** represent significance levels of 10%, 5%, and 1% respectively.

et al., 2020). This nuance informs targeted policies, unlike one-size-fits-all approaches in Southeast Asian contexts.

Overall, these findings carry significant practical implications for balancing rural labor mobility and agricultural environmental sustainability in China. First, the identified threshold in labor transfer highlights that policy interventions should be tailored to different stages of migration intensity—intensive pollution control measures are critical in early phases, while supporting adaptive practices (e.g., eco-friendly farming adoption) becomes more effective as migration scales up. Second, the dual role of non-farm income underscores the need for complementary policies. While increasing rural incomes is vital for poverty alleviation, coupling this with expanded agricultural socialized services (e.g., mechanized pest control, soil testing) can mitigate environmental costs. Finally, recognizing regional heterogeneity emphasizes that one-size-fits-all policies are ineffective, and interventions should account for local labor transfer patterns, agricultural practices, and service infrastructure to optimize both economic and ecological outcomes.

While this study enhances the understanding of how rural labor transfer influences ANPP. It is essential to recognize several limitations. First, the measurement of ANPP may not fully capture the environmental impacts of agricultural film, as this factor has not been integrated into the current indicator framework. Although the reuse of agricultural film exerts relatively minor effects on ANPP, residual film pollution has increasingly become a significant concern due to rising usage rates and insufficient recycling systems in certain regions. Therefore, future research should incorporate the adverse environmental consequences of residual agricultural film into ANPP assessments. Second, the analysis mainly focuses on the mechanisms related to non-farm income and agricultural socialized services, while other potential pathways—such as shifts in planting structures and demographic dynamics—remain underexplored. Further studies should investigate these additional mechanisms to gain a more comprehensive understanding of the complex relationship and develop more effective strategies for mitigating ANPP. Lastly, due to the unavailability of micro-level data, the current analysis is confined to macro-level interpretations based on aggregated data. Future research should prioritize the collection of detailed, granular data to enable more in-depth analyses.

## 6 Conclusion and policy implication

Drawing on comprehensive statistical data from 30 provinces in China spanning 2005–2020, this study systematically examines the impact of rural labor transfer on ANPP and its underlying mechanisms. Utilizing a robust analytical framework that incorporates fixed effects models, mediating and moderating effect models, instrumental variable estimation, and threshold regression analysis, we derive the following key findings: (i) Rural labor transfer exerts a positive influence on ANPP. Heterogeneity analysis reveals significant variations in this impact across different types of rural labor transfer and geographical regions. Specifically, year-round migrant labor demonstrates a substantially greater environmental impact compared to seasonal migrant labor. From the perspective of trans-geographical transfer, intra-provincial labor transfer shows the strongest correlation with ANPP, followed by inter-provincial transfer, while local transfer exhibiting insignificant impact. Regionally, the central region experiences the most pronounced effects, followed by the western and eastern regions, while the northeastern region shows no statistically significant impact.(ii) The relationship between rural labor transfer and ANPP exhibits a single threshold effect, demonstrating a non-linear pattern characterized by diminishing marginal impacts as the scale of labor transfer increases.(iii) Rural labor transfer significantly enhances non-farm income, which in turn contributes to ANPP, indicating that non-farm income serves as a mediating variable in this relationship.(iv) Agricultural socialized services play a crucial moderating role in this dynamic, effectively mitigating the positive impact of non-farm income on ANPP and thereby attenuating the overall environmental consequences of rural labor transfer.

These findings offer critical policy implications for mitigating ANPP. Specifically, the primary task is to vigorously develop rural secondary and tertiary industries in labor-exporting areas. Local governments can attract enterprises to set up factories in rural areas through measures such as tax incentives and land security guarantees, while financial institutions can provide targeted low-interest loans to support local non-agricultural entrepreneurship, thereby effectively creating employment opportunities nearby. This approach not only expands farmers' income channels and enhances their ability to resist risks, but also fundamentally reduces the tendency of extensive cultivation of arable land caused by large-scale and long-distance labor transfer, alleviating the indirect pressure on ANPP. Secondly, it is imperative to accelerate the construction and strengthening of a comprehensive, convenient, and efficient agricultural socialized service system. The government should increase financial input to support the network construction and service capacity improvement of service providers, with a focus on tilting resources to regions such as the central and western parts of China where the impact of labor transfer is significant. Service organizations need to innovate models and provide affordable green production trusteeship services and technical packages. Farmers should be encouraged to collectively purchase services through organized forms such as cooperatives to achieve economies of scale. This not only directly makes up for the shortcomings in field management after labor migration, but also effectively "offsets" the possible over-reliance on chemical inputs induced by the increase in non-farm income through professional and intensive services, significantly weakening the indirect promoting effect of rural labor transfer on ANPP. At the same time, continuous efforts should be made to promote the popularization and implementation of green agricultural technologies. Agricultural departments should collaborate with research institutions and promotion systems to develop and promote practical green technologies targeting major crops and pollution problems in different regions. Through various forms such as government-purchased services, project demonstrations, and targeted training, the rate of technology adoption and application effects should be effectively improved to reduce pollution loads at the source of production. Finally, policy design should reflect regional differences. For central regions with active intra-provincial labor transfer and western regions facing similar challenges, priority should be given to allocating socialized service resources and green technology promotion forces to accurately respond to their significant environmental effects of labor transfer.

## Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## Author contributions

YoY: Funding acquisition, Conceptualization, Data curation, Resources, Methodology, Writing – original draft, Investigation, Formal analysis. SH: Methodology, Writing – original draft, Formal analysis, Investigation, Conceptualization. FJ: Investigation, Resources, Writing – original draft, Formal analysis. LP: Supervision, Funding acquisition, Writing – review & editing. YaY: Writing – original draft, Funding acquisition, Supervision, Writing – review & editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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