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LAND TRANSFER AND GREEN PRODUCTIVITY SYNERGIES FOR SUSTAINABLE AGRICULTURE

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Highlights:
- we use the super-efficient SBM to measure agricultural green total factor productivity, tested by fixed-effects and mediation-effects models based on panel data of 30 Chinese provinces (2006–2023);
- agricultural land transfer increases agricultural green total factor productivity, with results robust to endogeity and robustness tests;
- mechanism test shows agricultural land transfer improves agricultural green total factor productivity via scale effect, rural labor flow and capital deepening;
- heterogeneity test reveals more obvious effects in central China, main grain-producing areas and planting areas.

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Abstract. The promoting effect of agricultural land circulation on the enhancement of agricultural green total factor productivity (AGTFP) and the high-quality development of China's agriculture still requires in-depth empirical verification. This study employs the super-efficiency SBM method to quantitatively evaluate AGTFP. Based on panel data from 30 provinces in China spanning the period 2005–2022, it conducts an empirical analysis using fixed-effects models and mediation-effects models. The main research conclusions are as follows: Firstly, the empirical findings indicate that agricultural land circulation has a positive impact on AGTFP, and this conclusion remains robust after undergoing endogeneity tests and robustness checks. Secondly, mechanism analysis reveals that agricultural land circulation effectively elevates the level of AGTFP by promoting economies of scale, accelerating the transfer of rural labor, and facilitating capital deepening, among other pathways (Hu et al., 2025). Meanwhile, economies of scale, labor mobility, and capital deepening also have common and synergistic effects. Thirdly, heterogeneity analysis demonstrates that the enhancing effect of agricultural land circulation on AGTFP is more pronounced in the eastern and central regions, major grain-producing areas, and cultivated regions. Based on the aforementioned research findings, it is recommended that China expedite the reform of its agricultural land circulation system to achieve a steady increase in AGTFP, thereby fostering the development of agriculture.

Keywords: agricultural land transfer, green total factor productivity in agriculture, scale effects, rural labor mobility, capital deepening.

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1. Introduction

Enhancing agricultural productivity is central to promoting the high-quality and modernized transformation of the agricultural sector (Cheng et al., 2025; Qu et al., 2018). In the current global context marked by escalating trade wars and persistent geopolitical tensions, ensuring food security has become a critical concern for all nations. In this regard, GTFP in agriculture plays a vital role (Ye et al., 2023) and serves as an essential pillar for building a strong socialist agricultural power (Bilewicz et al., 2022). The report of the *20th National Congress of the Communist Party of China* clearly states that "high-quality development is the top priority for achieving socialist modernization" (Li & Chen, 2022). Improving agricultural productivity is not only key to ensuring stable food production and farmer income (Harkness et al., 2023) but also a fundamental guarantee for revitalizing rural industries and increasing farmers' earnings (Guo & Liu, 2021). Meanwhile, promoting green agricultural development contributes significantly to enhancing the rural ecological environment and constructing livable countryside communities (Ma & Appolloni, 2025). Substantially improving agricultural total factor productivity (TFP) has become a major initiative of the Chinese government to ensure stable supplies of grain and other key agricultural products (Baig et al., 2023). However, it is noteworthy that the growth rate of China's agricultural TFP has slowed, and a significant gap remains compared to developed countries (Pan et al., 2022), particularly in terms of labor productivity, where China lags behind the United States, indicating substantial room for improvement (Hou et al., 2022). Given the reality of "a large country with smallholder farming" in China, developing appropriately scaled agricultural operations is regarded as one of the most effective strategies to enhance productivity and advance agricultural modernization (Dou et al., 2024). Therefore, for Chinese agriculture to achieve high-level development, both productivity enhancement and the acceleration of green transformation must proceed in tandem (Yuan et al., 2024). Agricultural green total factor productivity, as a comprehensive indicator of the coordination between agricultural output and ecological sustainability (Lyu et al., 2021; Wen et al., 2025), aligns closely with the Party's call to "strive to improve total factor productivity." Investigating its influencing factors thus holds significant value for promoting efficient and green agricultural transformation (He et al., 2021b).

Since the late 1970s, China has implemented the Household Responsibility System, a policy that significantly boosted farmers' enthusiasm for agricultural production and provided a positive pathway for China's economic growth as well as the revitalization of the rural economy during the early stages of reform and opening-up (Li et al., 2025; Xiao et al., 2024). However, during its implementation, this system overlooked the heterogeneity in production efficiency among farmers, resulting in a pattern of land management characterized by small and fragmented plots (Liu & Huo, 2024). Once the problem of subsistence was largely resolved, farmers' dependence on land gradually diminished, and a substantial portion of the rural labor force began to migrate to non-agricultural sectors (Moreda, 2023). Under circumstances where the transfer of agricultural land was strictly constrained, a dual contradiction emerged: on the one hand, some farmland became idle due to farmers transferring out of agriculture, and on the other hand, farmers seeking to expand their operations faced difficulties in acquiring additional land resources, leading to low land use efficiency (Rogers et al., 2021). In response, the Chinese government progressively improved policies and regulations governing the transfer of agricultural land (Liu et al., 2025a). The *Rural Land Contract Law*, promulgated in 2002, explicitly granted farmers the rights to subcontract, lease, exchange, and transfer contracted land. Subsequently, the *Administrative Measures for the Transfer of Rural Land Contractual Management Rights*, issued in 2005, further encouraged the circulation and transfer of agricultural land. Empirical data show that between 2005 and 2017, the proportion of farmland under transfer increased significantly from 4.40% to 37.30%. This indicates that farmland transfer has created favorable conditions for achieving economies of scale and enhancing production efficiency (Fei et al., 2021). However, it is noteworthy that China's agricultural operations are still predominantly smallholder-based, accounting for over 80% of total farming households (Duan et al., 2021; Liu et al., 2025b), with an average farm size generally less than 10 mu (approximately 0.67 hectares). Consequently, there remains a considerable gap in achieving full agricultural mechanization and modernization. This situation raises several important questions worthy of in-depth investigation: Has farmland transfer effectively promoted improvements in agricultural green total factor productivity? What are the specific mechanisms through which it influences technical efficiency and technological progress? Through which channels do transfer policies enhance agricultural production efficiency? Exploring these questions holds significant implications for refining China's farmland transfer policies.

Therefore, this article uses data from 30 provinces in China from 2005 to 2022 to empirically test the impact of agricultural land transfer on agricultural total factor productivity and the mechanisms that exist. Compared with existing literature, the marginal contribution of this article is as follows: firstly, this article deeply explores the impact mechanism of agricultural land transfer on green total factor productivity, not only identifying a single effect, but also revealing the synergistic effect of three mechanisms: scale effect, labor mobility, and capital deepening. Especially in the detailed analysis of synergistic effects, it emphasizes that the mechanism variables are not just overlapping effects. This multi-path and multi-level mechanism analysis method provides a new perspective for agricultural policy makers, helps to understand the complex driving mechanisms of agricultural systems, and points out the direction for further promoting industry development. Secondly, this article conducted a comprehensive heterogeneity test, revealing the differences in the impact of agricultural land transfer on agricultural green total factor productivity in different regions (such as the eastern and western parts, grain functional areas, planting and animal husbandry distribution areas). This analysis highlights the necessity of implementing differentiated policies in different regions and functional areas, providing targeted and effective policy recommendations.

2. Literature review

2.1. Research on the impact of agricultural land transfer on agricultural green total factor productivity

Over the past decades, a considerable volume of research has examined farmland transfer in China; nonetheless, investigations into how such transfers influence agricultural production efficiency at a mechanistic level remain relatively sparse. Zang et al. (2022) observed that enlarging farm size through land transfer encourages producers to shift toward specialized farming models. This adjustment compels farmers to upgrade traditional practices by adopting improved crop varieties and enhancing soil management, leading to better production outcomes (Luo et al., 2023). In contrast, Qian and Hong (2016) found that although transferring land contributes to higher land productivity, its effect on labor productivity is limited (Gao et al., 2022).

A major shortcoming of earlier analyses lies in their focus on single-factor indicators, such as labor or land productivity, which insufficiently capture the joint dynamics of multiple production elements (Zhao et al., 2021; Shen et al., 2022). To overcome this, more recent scholars have increasingly turned to TFP metrics to assess agricultural efficiency more comprehensively. For example, Pan et al. (2021), applying data envelopment analysis in regions including Beijing, Shanghai, and Guangdong, reported that while technical efficiency may initially decline post-transfer, overall TFP improves due to larger gains in scale efficiency. A similar conclusion was reached by Jiang et al. (2021), who emphasized the facilitating role of land transfer in enhancing TFP. However, Xie et al. (2022) offered a more complex view: based on provincial data, they found a non-linear relationship, where the impact of land transfer on TFP first rises and then falls — an inverted U-shaped pattern — while technical efficiency improves steadily throughout. Diverse findings have also emerged in studies addressing resource allocation (Ma et al., 2025). Challoumis (2024) argued that reallocating farmland optimizes resource use and boosts economic efficiency by adjusting market supply and demand. Conversely, Li and Lee (2021) identified inefficiencies, noting that highly productive farmers often operate on smaller plots, highlighting mismatches in current land distribution. In addition to efficiency outcomes, research has extended to other effects of land transfer, including enhancing rural household income (Li et al., 2021), improving farmers' welfare (Geffersa et al., 2022), and fostering agricultural investment (Pickson et al., 2025).

2.2. Research on the mechanism of agricultural land transfer on agricultural green total factor productivity

Recent scholarship has increasingly turned attention to exploring how farmland transfer shapes both agricultural production efficiency and environmentally sustainable farming practices. Regarding production efficiency, the majority of studies present a favorable assessment. Xie and Mei (2022) identified that farmland transfer enables the movement of land from less productive to more productive users, thereby improving the allocation of agricultural resources. Expanding on this argument, Belton et al. (2021) noted that this reallocation process contributes significantly to advancing agricultural mechanization. Yue et al. (2023) similarly demonstrated that transfer activities enhance productivity within farmers' core operational sectors. However, Gorgan and Hartvigsen (2022) cautioned that these efficiency improvements may be tempered by variables such as farmers' price expectations and risk attitudes associated with land transactions. Alternatively, Yuan and Wang et al. (2022) offered a contrasting perspective, asserting that farmland transfers in China are currently constrained by a phenomenon of "involution" and persistent land fragmentation, factors which together diminish production efficiency. When it comes to environmentally sustainable agricultural practices, academic views diverge more sharply. Du et al. (2023) and Wu et al. (2025) argued that transferring farmland may intensify environmental challenges by raising agricultural carbon emissions and increasing the use of environmentally harmful agrochemicals. Conversely, evidence presented by Yu et al. (2022) suggested that transfer activities alleviate land fragmentation, promote larger-scale farming operations, and thus lower the reliance on chemical fertilizers and pesticides. Complementary findings from He et al. (2021a) indicated that land consolidation through transfer encourages broader adoption of green agricultural technologies. Of particular note, Liu et al. (2023) reported that farmland transfer has a statistically significant effect.

In summary, although the academic community has accumulated fruitful research results on the transfer of agricultural land in China, the exploration of the mechanism of land transfer on agricultural production efficiency is still relatively limited. Existing research has mostly focused on describing the phenomenon of land transfer, interpreting policies, and simply evaluating its effects. However, there is a lack of systematic and in-depth analysis on how the complex mechanisms behind it affect various aspects of agricultural production efficiency. This makes our understanding of the intrinsic relationship between land transfer and agricultural production efficiency not comprehensive and accurate enough. Meanwhile, existing research mainly uses single factor indicators such as labor productivity or land productivity to measure agricultural output efficiency. Although this measurement method is simple and intuitive, it is difficult to comprehensively capture the comprehensive changes in the efficiency of various production factors. Therefore, given the limited research focus, measurement index limitations, and many divergent conclusions in the existing studies on the mechanism of land transfer on agricultural production efficiency, it is necessary to further conduct research to comprehensively, deeply, and accurately test the mechanism of land transfer on agricultural production efficiency, unify different research conclusions, and provide more reliable and effective basis for policy formulation and practical operation.

3. Theoretical analysis and research hypothesis

3.1. The impact of agricultural land transfer on green total factor productivity in agriculture

From the standpoint of land resource consolidation, the household contract responsibility system initially invigorated farmers' engagement in agricultural activities. However, over time, it inadvertently contributed to an increasingly fragmented land tenure structure. Such fragmentation has not only imposed significant constraints on the enhance of agricultural mechanization and large-scale farming—thereby undermining overall production efficiency—but has also indirectly encouraged excessive dependence on chemical inputs such as fertilizers and pesticides in the pursuit of short-term yield maximization, leading to notable ecological degradation in rural environments (Duan et al., 2024). Confronting these structural inefficiencies, the establishment and progressive enhancement of farmland transfer mechanisms has emerged as a critical strategy to facilitate more rational land use (Ying et al., 2025). As the institutional maturity of agricultural land transfer mechanisms has advanced, market-driven forces have assumed a more prominent role in orchestrating land resource allocation (Sun & Luo, 2026). Empirical evidence indicates that through partial or full transfer of landholdings, less productive farmers are able to disengage from labor-intensive agricultural production and redirect their labor toward non-agricultural sectors (Jiang et al., 2022). This reallocation process diversifies household income sources and improves financial resilience. Concurrently, households with greater productive capacity have leveraged land transfers to scale up their operations, thereby securing consistent gains in agricultural returns. As Long (2022) articulates, this evolving pattern reflects an efficiency-oriented redistribution of land resources, wherein farmland systematically shifts from less efficient to more efficient producers, promoting both productivity enhancement and rural economic transformation (Sun & Li, 2025a).

The progressive expansion of agricultural land transfer has markedly facilitated large-scale land consolidation, thereby enhancing the efficiency of land resource allocation within the agricultural sector. This structural shift has not only catalyzed the transition from fragmented, smallholder-based farming toward more centralized and specialized production systems, but has also triggered a fundamental transformation in agricultural production paradigms (Fang et al., 2021). The establishment of scaled-up operations has provided an enabling environment for the widespread adoption of mechanization and smart farming technologies, which, in turn, have substantially improved agricultural productivity. Moreover, large-scale farming practices enable greater precision in the application of agricultural inputs such as fertilizers and pesticides. This has proven effective in reducing input intensity, mitigating surface-level agricultural pollution, and laying a foundational basis for the enhancement of agro-ecological sustainability (Gao, 2024). In parallel, appropriately scaled agricultural operations have played a vital part in promoting the vertical integration and spatial extension of the agri-food value chain (Sun & Li, 2025b). This integration fosters synergistic development across the primary (Wang & Ma, 2024). Secondary, and tertiary sectors of the rural economy. Through the promotion of emerging sectors such as agri-processing, rural tourism, and multifunctional agriculture, this transformation not only diversifies the structure of the agricultural industry (Iannucci et al., 2022), but also creates additional income-generating avenues for rural households, thereby strengthening the economic viability and overall competitiveness of the agricultural sector (Niu et al., 2022). Consequently, moderate-scale agricultural operations serve as both a catalyst for agro-ecological restoration and a strategic driver of GTFP, playing an indispensable role in advancing the green transformation of agriculture. Accordingly, the following hypotheses are proposed:

Hypothesis 1: *Agricultural land transfer has an increasing effect on green total factor productivity in agriculture.*

3.2. Agricultural land transfer, economies of scale, and green total factor productivity in agriculture

The agricultural land transfer mechanism, as a strategic policy tool for optimizing resource allocation, plays a role in facilitating the systematic redistribution and efficient utilization of farmland among diverse agricultural entities (Xia et al., 2025). This institutional innovation addresses persistent structural issues associated with land underutilization and plot fragmentation, which have long constrained productivity within the framework of the household contract responsibility system (Zou et al., 2024). More importantly, it lays the groundwork for a transition toward scaled-up and intensified agricultural production models (Marin et al., 2022). As a cornerstone of modern agricultural transformation, large-scale and intensive farming serves as a critical engine for enhancing agricultural TFP and reflects the broader trajectory of contemporary agricultural modernization. In practical terms, land transfer enables farmers to expand operational scale, fostering economies of scale and promoting structural upgrading within the agricultural sector (Yang et al., 2021). This scaling-up process is primarily driven by emerging agricultural entities such as large-scale commercial farmers, family farms, specialized cooperatives, and agri-enterprises, all of which benefit from superior access to capital, advanced technologies, and modern management capabilities (Huang et al., 2024). The moderate expansion of farm size facilitates a more efficient reconfiguration of production factors—including labor, land, and capital—across broader spatial and organizational dimensions. This reallocation enhances overall production efficiency by approaching or achieving Pareto improvements, thereby contributing to both productivity gains and the long-term sustainability of agricultural development (Sun, 2025).

At the micro level, the agricultural land transfer mechanism enables the reallocation of land from farmers with relatively low marginal returns to those with higher productivity, thereby facilitating more efficient and rational utilization of land resources. For land recipients, the resultant expansion in operational scale contributes not only to economies of scale—reflected in reduced unit production costs (Song et al., 2022)—but also fosters technological upgrading and managerial innovation, which collectively enhance production efficiency and bolster market competitiveness. Nevertheless, the scaling-up process is not without risk. In instances where complementary factors of production—such as labor quality, technological capacity, capital availability, and managerial competence—fail to adapt concurrently with scale expansion, diminishing returns may arise. This condition, commonly referred to as "diseconomies of scale," may result in inefficiencies, misallocation of resources, and erosion of competitive advantage (Seif et al., 2024). Hence, suboptimal coordination of input factors can negate the anticipated benefits of scaling and even compromise overall productivity. Accordingly, while encouraging land consolidation and the intensification of agricultural operations, it is imperative to enhance farmers' comprehensive managerial capabilities and their capacity to manage risk (Zeng et al., 2025; Peng et al., 2025). Only through the strengthening of these institutional and human capital dimensions can the sustainable and robust development of the agricultural sector be assured (Bertolozzi-Caredio et al., 2021). Based on this rationale, the following hypotheses are proposed:

Hypothesis 2: *Agricultural land transfers increase green total factor productivity in agriculture by promoting large-scale operations and thus increasing total factor productivity in agriculture.*

3.3. Agricultural land transfer, labor mobility, and green total factor productivity in agriculture

The agricultural land transfer mechanism serves as a pivotal instrument in reconfiguring the distribution of production factors, particularly labor, within the rural economy. It facilitates the strategic reallocation of labor from households with comparatively low agricultural productivity to more lucrative employment opportunities in the secondary and tertiary sectors (Zhang, 2023). As part of this structural adjustment, a portion of the household workforce remains engaged in farming, while others pursue off-farm employment. This dual-labor arrangement not only supplements household income but also enables reinvestment in agriculture—through the acquisition of advanced equipment, improved inputs, and enhanced infrastructure—thus fostering material upgrading in agricultural production systems (Sen et al., 2021). Furthermore, the broader expansion of non-agricultural employment contributes to the acceleration of industrialization, potentially giving rise to the phenomenon of "industry supporting agriculture." In such cases, the transfer of capital, knowledge, and technology from industrial sectors aids in the modernization of agricultural practices and improves overall production efficiency (Danda, 2023).

However, this labor shift is not without adverse implications. Frequently, those who remain in agricultural production are older or less skilled individuals, resulting in a progressive aging of the rural workforce. This demographic shift may hinder the adoption of modern technologies and reduce the adaptability and productivity of labor in the agricultural sector (Baležentis et al., 2021). Consequently, under such circumstances, it remains uncertain whether agricultural productivity at the household level can be sustainably improved. In cases where all able-bodied members exit agriculture entirely, productivity becomes a non-issue for the household, yet from a regional or macroeconomic standpoint, this represents a net depletion of labor resources essential for maintaining agricultural output (Feng et al., 2025; Nanhthavong et al., 2022). Given the foundational role of agriculture in securing food supplies and fostering rural development, the long-term stability of agricultural labor must not be overlooked. Nevertheless, current evidence suggests that the facilitation of labor mobility through land transfer has yielded net positive outcomes for household livelihoods and rural transformation. Based on this reasoning, the following hypotheses are proposed:

Hypothesis 3: *Agricultural land transfer increases green total factor productivity in agriculture by increasing labor mobility, and thus.*

3.4. Agricultural land transfer, capital deepening, and agricultural green total factor productivity

The concept of agricultural capital deepening—defined as the increasing ratio of capital stock relative to labor input in agricultural production—has emerged as a hallmark of modern agricultural transformation (Mukherjee et al., 2022). This shift is instrumental in driving improvements in green total factor productivity (GTFP) by enhancing both input efficiency and technological intensity. Given the centrality of land as a fundamental production factor, its efficient utilization and strategic redistribution are critical. Agricultural land transfer, as a key institutional mechanism for optimizing land allocation, has fundamentally reshaped the landscape of agricultural production. By enabling less productive farmers to exit the sector and reallocate their labor to non-agricultural activities, land transfer facilitates the reorganization of production resources and enhances labor mobility across sectors. Consequently, farmland becomes concentrated in the hands of more capable and efficient operators (Martínez-Valderrama et al., 2024), thus supporting productivity gains and more effective capital utilization.

The relationship between land transfer and capital deepening manifests in several key ways. First, the reallocation of land resources to higher-performing producers promotes operational scale expansion (Foster & Rosenzweig, 2022). This scaling effect incentivizes additional investment in land improvement and capital-intensive technologies, such as advanced machinery, high-efficiency inputs, and precision agriculture practices (Wang & Cheng, 2022). As a result, the mechanization rate and technological sophistication of production processes increase substantially, accelerating capital accumulation in agriculture (Lu et al., 2024). Moreover, the evolution of land transfer policy frameworks has significantly reduced transaction barriers. Historically, high transaction costs—stemming from institutional rigidities and underdeveloped land markets—deterred active participation in land transfers (Ma et al., 2023). However, with ongoing policy refinement and improved market transparency, these barriers have diminished, making transactions more accessible and efficient (Quan et al., 2024). This regulatory progress has stimulated greater capital inflows into agriculture, particularly in long-term investments such as irrigation infrastructure, storage systems, and mechanized facilities (Wang et al., 2021). These fixed asset investments not only bolster the resilience and sustainability of agricultural systems but also reinforce the material foundation necessary for capital deepening (Ren et al., 2024). Taken together, these developments underscore the transformative potential of land transfer mechanisms in enhancing the intensity and productivity of capital use in agriculture. Consequently, the following hypotheses are put forward:

Hypothesis 4: *Agricultural land transfers increase green total factor productivity in agriculture by facilitating capital deepening and thus increasing total factor productivity in agriculture*.

3.5. The synergistic effect of agricultural land transfer and agricultural green total factor productivity mechanism

The impact of agricultural land transfer on improving agricultural green total factor productivity may be a multifaceted process, involving the combined effects of three main channels: economies of scale, labor mobility, and capital deepening. Through the comprehensive impact of these three channels, land transfer actually provides a more optimized and sustainable framework for agricultural production. Firstly, land transfer directly promotes the realization of economies of scale. Through land transfer, small-scale and scattered land can be integrated. This integration helps to form larger scale arable land, providing a platform for new agricultural management entities such as "large-scale growers", "family farms", and "professional cooperatives" to showcase their management and technological advantages. At the same time, land transfer has promoted the optimized allocation of labor mobility. After the concentration of land, those laborers who were engaged in farming and had low production efficiency on their own small plots of land were liberated. These laborers can flow towards the secondary and tertiary industries or more efficient agricultural entities, which not only improves the overall labor market mobility but also increases the non-agricultural income of rural households. And this income, in turn, will be further invested in agricultural production, improving agricultural equipment, purchasing high-quality seeds and fertilizers, and so on. The recycling of this income effectively enhances the material foundation of agricultural production. In addition, the labor force left behind engaged in agriculture can relatively concentrate on using these resources and funds, focusing on improving agricultural production efficiency, promoting agricultural technological progress, and further promoting the improvement of green total factor productivity. Finally, land transfer also catalyzed the process of capital deepening. The concentration of land towards efficient producers gives these producers greater motivation and ability to invest capital. The purchase of advanced agricultural machinery and equipment and the construction of agricultural infrastructure have become possible, greatly improving the mechanization level and technological content of agricultural production. Abundant capital investment not only enhances the risk resistance of agriculture, but also improves the efficiency of resource utilization throughout the entire production process. At the same time, the improvement of land transfer policies has reduced transaction costs and provided smoother environmental support for the deepening of capital, making the role of capital in agriculture more prominent and comprehensive.

Therefore, the synergistic effect of scale effect, labor mobility, and capital deepening in agricultural land transfer has jointly promoted the improvement of green total factor productivity in agriculture. Large scale operation reduces production costs and improves resource utilization efficiency; Labor mobility has brought higher non-agricultural income and technological diffusion; Capital deepening makes agricultural production more modern and efficient through the improvement of equipment and infrastructure. These three channels do not operate independently, but promote and complement each other, jointly accelerating the improvement of agricultural green total factor productivity. For this purpose, assume the following:

Hypothesis 5: *Agricultural land transfer improves agricultural green total factor productivity through the synergistic effect of scale effect*, *labor mobility*, *and capital deepening*.

4. Research design

4.1. Measurement of total factor productivity in agriculture

(1) Super-Efficient SBM Measurement Models

Previous research has predominantly employed DEA to evaluate TFP in agriculture, largely due to its non-parametric nature, which eliminates the need to specify a functional form of the production technology in advance. This characteristic allows the DEA approach to effectively mitigate the influence of subjective or perception-based biases, thereby enhancing the objectivity of efficiency assessments. In line with this methodological advantage, the present study utilizes DEA to measure green total factor productivity (GTFP) in agriculture. Nevertheless, traditional radial and angular DEA models may result in biased estimations—often overstating efficiency levels—because they fail to account adequately for slacks in input and output variables. These limitations may lead to a divergence between the estimated and actual performance levels. To address this issue and enhance the robustness of the measurement framework, this study adopts the super-efficiency Slack-Based Measure (SBM) model. The SBM model effectively accounts for non-radial slacks and input-output imbalances, thereby providing a more accurate and discriminative evaluation of agricultural productivity. The specific formulation of the model is as follows:

$$AGTFP = \min \frac{1-\frac{1}{m}\times\sum_{i=1}^{m}\frac{S_i^-}{X_i}}{1+\frac{1}{S_1+S_S}\times\left(\sum_{r=1}^{S_1}\frac{S_r^g}{Y_r^g}+\sum_{k=1}^{S_2}\frac{S_k^b}{Y_k^b}\right)}, \quad (1)$$

where i = 1, 2, ..., m; r = 1, 2, ..., S_1; k = 1, 2, ..., S_2.

Subject to $X_0 = X\times\lambda + S^-$

$$Y_0^g = Y^g\times\lambda - S^g;$$
$$Y_0^b = Y^b\times\lambda + S^b; \quad (2)$$
$$S^- \geq 0, S^g \geq 0 S^b \geq 0.$$

(2) GML Index

While the SBM model utilized in this study facilitates the evaluation of each decision-making unit's GTFP under a given technological frontier, it inherently reflects a static measure of technical efficiency at a specific point. However, given the inherently dynamic and temporal nature of agricultural production, reliance solely on static efficiency estimates may fail to capture intertemporal changes in productivity. To address this limitation and more accurately reflect the temporal evolution of efficiency, this study incorporates a global non-radial DEA model that accounts for undesirable outputs to construct the Malmquist–Luenberger productivity index (GML index). This dynamic approach enables the assessment of changes in GTFP over time by considering both technological progress and efficiency change. The formal specification of the model is as follows:

$$GML^{t,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1+D_G^T\left(x^t, y^t, b^t\right)}{1+D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}, \quad (3)$$

where if $GML^{t,t+1} < 1$, it indicates that the agricultural green total factor productivity decreases; when $GML^{t,t+1} > 1$, it indicates that the agricultural green total factor productivity decreases rise. Since GML = BPC × EC, it is possible to decompose agricultural green total factor productivity into technical progress (BPC) and technical efficiency (EC).

$$GML^{t,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1+D_G^T\left(x^t, y^t, b^t\right)}{1+D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} =$$
$$\frac{1+D_C^t\left(x^t, y^t, b^t\right)}{1+D_C^t\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}\times\left[\frac{\frac{1+D_G^T\left(x^t, y^t, b^t\right)}{1+D_C^t\left(x^t, y^t, b^t\right)}}{\frac{1+D_C^t\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}{1+D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}}\right] =$$
$$EC^{t,t+1}\times BPC^{t,t+1}. \quad (4)$$

Among them, the values of $GML^{t,t+1}$, $EC^{t,t+1}$ and $BPC^{t,t+1}$ are all greater than 0. A value greater than one reflects positive growth in GTFP, suggesting that improvements have occurred in either technological progress, technical efficiency, or both. In contrast, a value below one indicates a regression in GTFP, signifying a decline in technological advancement, efficiency levels, or overall productivity within the agricultural sector.

4.2. Input and output indicators of green total factor productivity in agriculture

In the context of agricultural production, while the objective is to generate desirable outputs that align with principles of environmental sustainability, such processes inevitably produce undesirable outputs as by-products—primarily due to the intensive application of chemical inputs such as fertilizers and pesticides. These lead to negative externalities including pesticide residue-induced soil contamination and nutrient runoff resulting in land degradation. To comprehensively assess GTFP, this articles incorporates both desirable and undesirable outputs into the measurement framework. Furthermore, GTFP is decomposed into two core components: technological progress and technical efficiency. The detailed specification of input and output indicators used in the analysis is presented in Table 1.

Table 1. Input and output indicators of green total factor productivity in agriculture

Type of indicator	Name (of a thing)	Hidden meaning	Unit (of measure)
Input indicators	Agricultural labor inputs	Employees in the primary sector	All the people
	Agricultural land inputs	Sum of area sown under crops and area under aquaculture	Thousand hectares
	Agricultural fertilizer inputs	Agricultural fertilizer use (pure)	tons
	Agricultural machinery inputs	Gross power of agricultural machinery	Kilowatt (unit of electric power)
	Agricultural diesel inputs	Agricultural diesel use	Tons
	Agricultural plastic film inputs	Agricultural plastic film use	Tons
	Pesticide inputs	Pesticide use	Tons
	Agricultural water inputs	Effective irrigated area	Thousand hectares
Output indicators	Expected outputs	Gross output value of agriculture, forestry, livestock and fisheries	Billions
	Non-expected outputs	Agricultural carbon, sulfur, phosphorus and other emissions	Tons

4.3. Results of green total factor productivity measurements in agriculture

Figure 2 illustrates the trajectory of agricultural GTFP, benchmarked to the base year 2004. The curve is derived by calculating the provincial average of GTFP values across all sampled regions. As shown, the GTFP index remains consistently above unity throughout the observation period, suggesting a year-on-year improvement in the green productivity of China's agricultural sector. This upward trend implies that, over time, agricultural production has either become more effective in generating desirable outputs or has achieved reductions in undesirable outputs, thereby enhancing the overall eco-efficiency of agricultural practices.

According to the formula $GML = EC \times BPC$, agricultural green total factor productivity is decomposed into technical efficiency and technical progress to explore the intrinsic causes of agricultural green total factor productivity in China. As illustrated in Figure 1, during the sample period from 2006 to 2023, the contribution of technological progress consistently exceeds that of technical efficiency in driving GTFP growth in China's agricultural sector. This indicates that advancements in technology have served as the primary engine behind improvements in agricultural green productivity. Several factors may account for this pattern. The rapid pace of industrialization has facilitated large-scale labor migration from rural to urban areas, resulting in a shortage of younger, skilled labor in agriculture. Consequently, the aging agricultural workforce constrains the sector's ability to absorb and efficiently utilize new technologies and knowledge. Moreover, the relatively low economic returns from farming, compared to non-agricultural employment, further reduce incentives for active engagement in modern agricultural practices, particularly among smallholder farmers. These structural challenges have impeded gains in technical efficiency. In contrast, sustained investment in agricultural mechanization, policy-driven technological upgrades, the diffusion of improved agricultural inputs, and the expansion of large-scale farming have collectively fostered notable progress in green agricultural technologies. As a result, the observed improvements in GTFP during the period under review are primarily attributed to technological progress rather than improvements in technical efficiency.

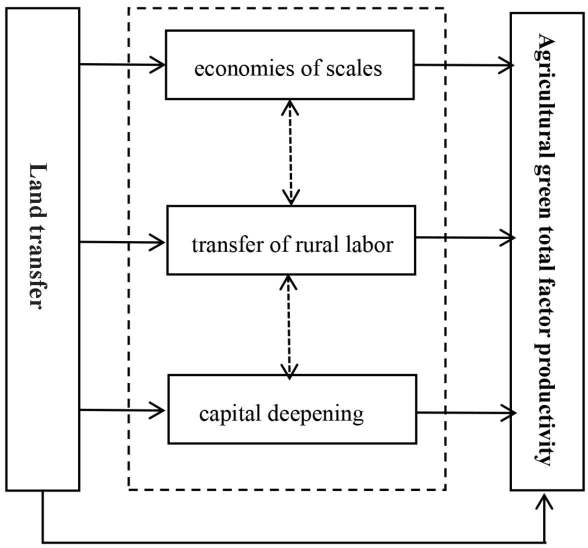

Figure 1. The mechanism of land transfer on agricultural green total factor productivity

4.4. Selection of variables

4.4.1. Explained variable

GTFP in agriculture is assessed in this study using the super-efficiency Slack-Based Measure (SBM) model. This approach enables the decomposition of GTFP into two distinct components: technical efficiency (GTC) and technological progress (GEC), thereby allowing for a more granular analysis of the drivers behind productivity dynamics in environmentally sustainable agricultural development.

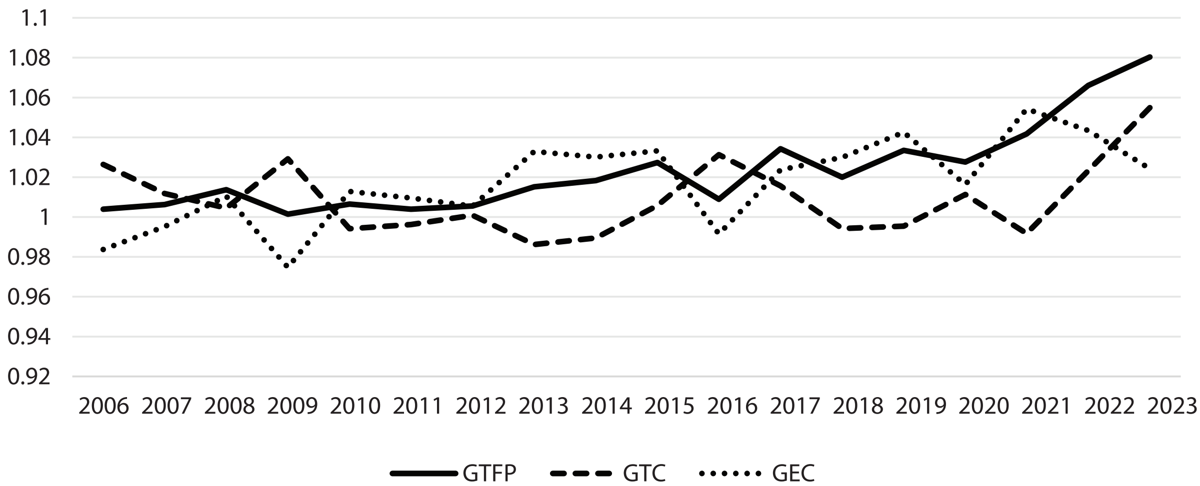

Figure 2. Trend graph of total factor productivity and its decomposition terms

4.4.2. Explanatory variable

Agricultural Land Transfer (FD). This variable is defined as the ratio of the area of family-contracted arable land transferred out to the total area of family-contracted arable land within each province. Generally speaking, agricultural land transfer should consider both transfer in and transfer out aspects. However, for the same region, the farmer whose land is transferred in is another farmer whose land is transferred out, and the two are numerically consistent. Considering the development of agricultural management entities, farmers are the only entities transferring land out, but not the only entities transferring land in, which will result in certain noise in the land transfer indicators. Therefore, this article considers agricultural land transfer from the perspective of land transfer. Of course, there are certain limitations to considering only from the perspective of transfer out. Simply focusing on the "transfer out" of land and neglecting the "transfer in" side can lead to incomplete data. This definition reflects more changes on the land supply side, but does not fully reflect the land demand side, that is, how land recipients use these lands for production. The scale expansion of the land transfer party and its specific contribution to productivity cannot be fully captured through the "transfer out" data.

4.4.3. Mediating variables

(1) Scale of Operation (sca): This indicator is defined as the ratio of total crop sown area to labor input in the primary sector, reflecting the degree of land-use intensification per unit of agricultural labor. (2) Labor Mobility (lab): Measured as the proportion of rural laborers engaged in non-agricultural employment relative to the total rural labor force, this variable captures the extent of off-farm labor migration. (3) Agricultural Capital Deepening (ljz): This is represented by the ratio of agricultural capital stock to primary industry labor input, serving as a proxy for capital intensity in agricultural production. The estimation of agricultural capital stock follows the perpetual inventory method, as outlined in Hou Mingli's research, which accounts for capital accumulation and depreciation over time.

4.4.4. Control variables

Referring to existing research, this article selects the following variables as control variables. (1) Per capita Gross Domestic Product (GDP), measured by the ratio of the GDP of each province to the total population. Per capita GDP is a comprehensive indicator of a region's economic development level, which can reflect the region's economic strength and development potential. The process of improving agricultural green total factor productivity is often accompanied by the introduction of technology and investment of funds, which depend on the economic development status of the region. (2) Rural population (rpo), measured by the ratio of rural population to year-end resident population. The proportion of rural population reflects the urban-rural population structure of a region and has a significant impact on the allocation of labor resources. Agricultural production relies on sufficient quantity and quality of labor, and changes in population structure may be an important factor affecting the supply, flow, and utilization efficiency of agricultural labor. A higher proportion of rural population in a region may affect agricultural production efficiency due to a more abundant supply of agricultural labor, and may also reflect a lack of non-agricultural employment opportunities. (3) Agricultural water use (wag) is measured by the ratio of total agricultural water use to total water use. Agricultural water use symbolizes the efficiency of key resource utilization and environmental sustainability in agricultural production. The optimized utilization of water resources plays a key role in promoting the development of green agriculture. Efficient agricultural water management can reduce resource waste and environmental pollution, thereby improving the green total factor productivity of agricultural production. (4) The degree of agriculturalization (dag) is a measure of the proportion of agricultural added value to regional gross domestic product. This indicator measures the proportion of agricultural added value relative to regional GDP, reflecting the proportion of agriculture in a region's economic structure. The changing role of agriculture in the overall economic output may affect resource allocation priorities and policy preferences. The degree of agriculturalization often affects the level of technological adoption and resource input in agricultural production activities, thus affecting green total factor productivity. (5) Mechanical density (med) is measured by the ratio of the total power of agricultural machinery to the added value of agriculture. Mechanization is an important symbol of agricultural modernization, and high mechanical density is usually accompanied by higher productivity and effective allocation of resources. The proportion of total power of agricultural machinery to agricultural added value has a significant impact on the process of production scale and intensification, and is a key factor in promoting technological progress and improving production efficiency. (6) The proportion of the primary industry (psi) is measured by the ratio of the added value of the primary industry to the added value of the secondary and tertiary industries. The proportion of the added value of the primary industry to that of other industries (secondary and tertiary industries) can reflect the stage and structural characteristics of the overall economic development of a region.

In the process of shifting the economic focus from the primary industry to the secondary and tertiary industries, it may prompt resources and policies to tilt towards more advanced agricultural technologies, promoting green agricultural development.

The descriptive statistics of variables are shown in Table 2. The mean of agricultural green total factor productivity is 1.037, with a standard deviation of 0.092. This mean indicates that the agricultural green total factor productivity during the sample period was slightly higher than the benchmark year, demonstrating an

Table 2. Descriptive statistics of variables

Variable name	Symbol	Obs	Mean	Std. Dev.	Min	Max.
Green total factor productivity in agriculture	gtfp	540	1.034	0.092	0.912	1.804
Technical efficiency	gtc	540	1.0013	0.082	0.598	1.786
Technological progress	gec	540	1.033	0.081	0.675	1.702
Agricultural land transfer	fd	540	25.24	18.505	1.355	91.111
GDP per capita	gdp	540	2.138	21.059	0.049	12.951
Rural population	rpo	540	0.437	0.14	0.104	0.731
Water for agriculture	wag	540	0.6	0.178	0.065	0.952
Degree of agriculturalization	dag	540	0.045	0.043	0.003	0.159
Mechanical density	med	540	0.615	0.254	0.211	1.416
Percentage of primary sector	psi	540	0.106	0.057	0.002	0.328

overall improvement in agricultural production efficiency. However, the standard deviation shows a certain degree of variability in agricultural efficiency between regions. The minimum value is 0.912 and the maximum value is 1.804, indicating that in some areas, the agricultural green total factor productivity is significantly lower or higher than the mean, suggesting that there may be special production conditions or policy influences in these areas. The mean of agricultural land transfer (fd) is 25.24, with a standard deviation of 18.505: this figure indicates significant differences in agricultural land transfer among provinces. The minimum value is 1.355 and the maximum value is 91.111, indicating that land transfer is very common in some areas but extremely rare in others, which may reflect differences in policy implementation or natural conditions. The average per capita regional gross domestic product (GDP) is 2.138, with a standard deviation of 21.059. This is an important economic indicator, and surprisingly, its standard deviation is much larger than the mean, indicating a serious imbalance in economic development levels between regions. The minimum value is 0.049 and the maximum value is 12.951, and this difference may affect agricultural technological progress and resource allocation in different regions. The average proportion of rural population (rpo) is 0.437, with a standard deviation of 0.14, indicating that there is still a large rural population in most areas, which may affect the supply of agricultural labor. The minimum and maximum values are 0.104 and 0.731, respectively: This variability may be related to the level of urbanization and economic development stage in the region. The mean and standard deviation of the proportion of agricultural water use (wag) are 0.6 and 0.178, respectively, indicating that agricultural water use occupies an important position in various water use categories, and there are differences in water use efficiency in different regions. The mean of agricultural production structure (SAP) is 1.966, with a standard deviation of 0.314, indicating significant changes in agricultural production structure, but still dominated by traditional agriculture, forestry, animal husbandry, and fisheries. The average degree of agriculturalization (dag) is only 0.045, with a standard deviation of 0.043, indicating that agriculture has a relatively low proportion in the economy, but some regions may have higher levels of agriculturalization. The mean mechanical density (med) is 0.615 with a standard deviation of 0.254, indicating significant regional differences in the process of agricultural mechanization and suggesting that the level of machinery is relatively high in certain regions. The average proportion of primary industry (psi) is 0.106, with a standard deviation of 0.057. The low mean reflects the relatively weak contribution of agriculture to the economy, but some regions still heavily rely on the primary industry of agriculture.

In summary, the descriptive statistical analysis in Table 2 reveals significant differences in agricultural total factor productivity and its influencing factors among provinces in China. This difference is not only related to the natural conditions, policy implementation efforts, and economic development levels of each region, but also reflects that in the process of promoting agricultural scale, mechanization, and technology, different regions have different starting points, which have led to different production efficiency results. This provides important background and support for further in-depth research on the mechanism and impact of land transfer on agricultural productivity.

4.5. Modeling

4.5.1. Baseline regression model

To empirically assess the effect of agricultural land transfer on GTFP in agriculture, this study employs a two-way fixed effects model incorporating both time and individual (province-level) heterogeneity. The econometric specification is as follows:

$$tfp_{i,t} = \beta_1 fd_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t}, \tag{5}$$

where $tfp_{i,t}$ denotes the agricultural green total factor productivity of province i in year t, $fd_{i,t}$ denotes the agricultural land transfer of province i in year t, $Z_{i,t}$ denotes the control variables, u_i denotes the individual fixed effects, ϱ_t denotes the time fixed effects, α denotes the constant term, and $\varepsilon_{i,t}$ denotes the randomized perturbation term.

4.5.2. Mediation effects model

To investigate the underlying mechanism through which agricultural land transfer influences GTFP in agriculture, this study employs a mediation effect analysis. Drawing on the methodological framework proposed by Kaya et al. (2021), we adopt a three-step estimation approach. Compared with conventional single-method mediation tests—such as those developed by Baron and Kenny or the Sobel test—the improved mediation model used in this study offers significant advantages. Specifically, it enhances statistical power while effectively controlling for both Type I and Type II errors. The empirical strategy for testing the mediating pathway is outlined as follows:

$$sca_{i,t} / lab_{i,t} / ljz_{i,t} = \beta_1 fd_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t}; \quad (6)$$

$$tfp_{i,t} = \beta_1 fd_{i,t} + \sigma_1 sca_{i,t} / lab_{i,t} / ljz_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t}, \quad (7)$$

where $sca_{i,t}$, $lab_{i,t}$, $ljz_{i,t}$ denotes scale effects, rural labor mobility, and structural effects, respectively. The remaining variables are consistent with the baseline regression.

4.6. Data sources

Due to data availability, this study constructs a balanced panel dataset covering 30 provincial-level regions in China (excluding Hong Kong, Macao, Taiwan, and Tibet) over the period from 2006 to 2023. Data on the output value of agriculture, forestry, animal husbandry, and fishery are sourced from the China Tertiary Industry Statistical Yearbook. Information regarding the operational area of contracted arable land and its transfer is drawn from successive volumes of the China Rural Management Statistical Annual Report. Input-output indicators and control variables are obtained primarily from the China Statistical Yearbook and the China Rural Statistical Yearbook. For missing values, supplementary data were retrieved from the corresponding provincial statistical yearbooks and official statistical bulletins. Furthermore, all monetary values were deflated to constant 2010 prices using 2010 as the base year, thereby ensuring data comparability over time.

5. Empirical findings and analysis

5.1. Benchmark regression results on the impact of agricultural land transfer on green total factor productivity in agriculture

Table 3 presents the baseline regression results assessing the effect of agricultural land transfer on GTFP in agriculture. Columns (1) and (2) report the estimates without and with control variables, respectively. The empirical findings indicate that agricultural land transfer exerts a statistically significant and positive effect on agricultural GTFP at the 1% significance level across both model specifications. This provides robust support for Hypothesis 1 proposed in this study. The underlying mechanism may be explained as follows: First, the process of land transfer facilitates the reallocation of farmland from less productive to more efficient farming entities, enabling more contiguous and large-scale land operations. This promotes the optimal allocation of production inputs, thereby reducing both production and management costs, and enhancing economies of scale. Second, as farm size expands, producers are better positioned to overcome the technological limitations associated with small-scale farming. This transformation encourages the adoption and utilization of modern agricultural technologies, which in turn improves production efficiency and drives growth in green total factor productivity.

Table 3. Benchmark regression results

Variables	(1)	(2)
	tfp2	tfp2
fd	0.177***	0.163***
	(6.703)	(3.561)
gdp		–1.20e-06***
		(–2.830)
rpo		–0.494***
		(–4.156)
wag		0.142
		(1.576)
dag		–0.0367
		(–0.237)
med		0.0271
		(0.732)
psi		1.222***
		(5.103)
individual fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Constant	0.992***	1.008***
	(131.2)	(12.39)
Observations	540	540
R-squared	0.081	0.173
Number of id	30	30

Note: *** indicates significance at the 1% level. The values in parentheses are *t*-values.

5.2. Impact of agricultural land transfer on the sub-efficiency of green total factor productivity in agriculture

To further investigate the underlying mechanisms through which agricultural land transfer influences GTFP, we employ the DEAP 2.1 software to decompose GTFP into technical efficiency (TEC) and technological progress (TE). Table 4 reports the regression results, with Columns (1) and (2) corresponding to TEC and TE, respectively. The results reveal that the coefficient of land transfer is significantly positive at the 1% level for technical efficiency, whereas its impact on technological progress is statistically insignificant. These findings suggest that the enhancement in GTFP driven by land transfer primarily operates through improvements in technical efficiency, rather than through advancements in technology.

Several factors may account for the limited effect of land transfer on technological progress. First, the agricultural land transfer market in China remains underdeveloped. Due to the vast geographical heterogeneity and incomplete market mechanisms, information asymmetry prevails, making it difficult to achieve optimal land matching between transfer parties. This inefficiency hinders the effective allocation of land resources and restricts the dissemination of advanced agricultural technologies, especially in rural and remote areas. Second, farmer concerns about livelihood security post-transfer may reduce their willingness to adopt new and potentially risky technologies. This conservative approach often favors traditional practices, slowing the pace of technological innovation. Third, legal and policy ambiguities surrounding land transfer further contribute to uncertainty. Vague land ownership regulations and potential disputes may discourage long-term investment in agricultural technology. Lastly, certain adverse effects, such as excessive capital deepening or technology-market mismatches, may inhibit technological progress despite apparent improvements in technical capacity.

Conversely, the positive impact of land transfer on technical efficiency can be attributed to several channels. First, land consolidation through transfer allows for scale expansion and more continuous land operation, which facilitates mechanization and the use of advanced technologies, thereby improving production efficiency. Second, the emergence of new agricultural business entities—such as family farms and cooperatives—enhances the organizational capacity to adopt and implement modern agricultural practices. These entities are more likely to engage in innovation, invest in sustainable technologies, and pursue environmentally friendly farming methods. Third, land transfer promotes more efficient allocation of production inputs—land, labor, and capital—across regions and actors, contributing to the structural upgrading of the agricultural sector and fostering green development. Finally, the stability associated with scaled and specialized farming reduces vulnerability to climate and market risks, while the increased use of environmentally sound practices reduces chemical input and improves ecological sustainability (Tong et al., 2025).

In sum, agricultural land transfer contributes to higher green total factor productivity primarily by enhancing technical efficiency through mechanisms such as land consolidation, innovation facilitation, improved resource allocation, and increased production resilience.

Table 4. Impact of agricultural land transfer on the sub-efficiency of green total factor productivity in agriculture

Variables	(1)	(2)
	te	tec
fd	0.0184	0.156***
	(0.403)	(3.682)
gdp	–7.68e-07*	–8.18e-07**
	(–1.826)	(–2.082)
rpo	–0.204*	–0.392***
	(–1.732)	(–3.557)
wag	0.00703	0.137
	(0.0788)	(1.639)
dag	–0.0411	–0.0673
	(–0.268)	(–0.469)
med	–0.0191	0.0503
	(–0.521)	(1.468)
psi	0.476**	1.053***
	(2.008)	(4.749)
individual fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Constant	1.069***	0.957***
	(13.26)	(12.71)
Observations	540	540
R-squared	0.021	0.179
Number of id	30	30

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values.

5.3. Endogeneity test

The baseline regression results presented in this study may be subject to endogeneity concerns, primarily due to potential reverse causality. Specifically, regions with higher levels of GTFP in agriculture may be more likely to engage in land transfer activities, thereby resulting in higher land transfer rates. In addition, unobserved factors—such as omitted variables—may also bias the estimated coefficients. To address these endogeneity issues, we adopt two complementary identification strategies.

First, we employ the system Generalized Method of Moments (GMM) estimator. Given that agricultural GTFP is inherently dynamic, its current value may be influenced by its past performance. To account for this temporal dependence and to mitigate potential omitted variable bias, we include a one-period lag of agricultural GTFP in the fixed-effects model, thereby transforming it into a dynamic panel specification. This approach allows us to control for the persistence of GTFP and to correct for potential endogeneity. The estimation results, reported in Column (1) of Table 5, show that the AR(1) and AR(2) tests confirm the presence of first-order autocorrelation and the absence of second-order autocorrelation in the differenced residuals, validating the application of the system GMM method. Furthermore, the Sargan test does not reject the null hypothesis, indicating that the chosen instruments are valid. Importantly, the estimated coefficient of agricultural land transfer remains significantly positive at the 1% level, confirming the robustness of the main findings.

Second, we apply the instrumental variable (IV) approach to further mitigate endogeneity concerns arising from potential simultaneity between land transfer and agricultural GTFP.

Following Huo and Chen (2022), we construct an instrument using the average level of land transfer in geographically adjacent provinces in the same year. This instrument satisfies two important conditions. On the relevance side, policy coordination and regional spillover effects—especially those shaped by national rural development strategies such as China's No.1 Central Document—are likely to create similarities in land transfer activity across neighboring provinces. Thus, land transfer practices in adjacent provinces are expected to influence those within a given province. The level of land transfer in neighboring provinces may affect the scale of agriculture in neighboring provinces through regional economic activities and policies. Due to similar natural conditions and economic development backgrounds in neighboring regions, the land transfer methods are easily influenced by the experiences of neighboring provinces. Therefore, considering geographical proximity can reasonably capture the expansion trend of land transfer. Neighboring provinces often have similar policy implementation environments, indicating the possibility of horizontal learning and imitation effects in policy implementation. The consistency and interactivity of policy implementation between regions can be indirectly revealed through land transfer data from neighboring provinces. On the exclusion side, the GTFP level in a given province is unlikely to directly affect land transfer activities in neighboring provinces, thereby ensuring instrument exogeneity. Although technology or information may spread between provinces, actual land transfer is often limited by specific geographical and legal boundaries. For example, land management systems and legal restrictions are usually different within each province, which limits other provinces from directly following the land transfer model of productivity first provinces. Meanwhile, the market conditions, social culture, and farmers' business motivations in each province are multivariate, and agricultural land transfer activities are often determined by local specific supply and demand relationships and social norms. Therefore, although changes in productivity in our province may convey experience and information, the driving force of land transfer is difficult to directly affect other provinces. Column (2) of Table 5 presents the first-stage regression results, confirming a statistically significant and positive association between the instrumental variable and the endogenous regressor (land transfer). Column (3) shows the second-stage regression results, which indicate that, even after instrumenting for land transfer, the estimated effect on agricultural GTFP remains significantly positive. This provides further empirical support for the validity and robustness of the causal relationship identified in this study.

Of course, there are also certain limitations to using this instrumental variable. Although the improvement of productivity in this province usually directly affects land transfer within the province, technology and management experience have the potential for cross regional dissemination. Technology spillover may invisibly affect farmers or agricultural enterprises in neighboring provinces through training, cooperative projects, or industry alliances. The dissemination of this technology or knowledge can affect the production efficiency and land transfer decisions of neighboring provinces. In future research, we will also try our best to find more suitable instrumental variables

Table 5. Endogeneity test

Variables	(1)	(2)	(3)
	tfp	fd	tfp
fd	0.147***		0.146*
	(2.919)		(1.742)
xfd		0.130***	
		(7.91)	
L.tfp	0.115**		
	(2.321)		
gdp	−1.09e-06**	3.35e-06***	−3.94e-07
	(−2.354)	(10.46)	(−1.220)
rpo	−0.434***	−0.777***	−0.119
	(−3.393)	(−11.79)	(−1.260)
wag	0.119	−0.279***	0.221***
	(1.240)	(−7.28)	(4.443)
dag	0.0123	0.073	−0.254
	(0.0768)	(0.35)	(−1.024)
med	0.0179	−0.080	−0.00842
	(0.460)	(−3.75)	(−0.611)
psi	1.121***	0.780**	0.270
	(4.001)	(2.30)	(1.426)
individual fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Constant	0.900***	0.780***	0.916***
	(8.873)	(23.79)	(16.03)
AR(1)	0.002		
AR(2)	0.336		
Sargan	37.216 [0.538]		
Kleibergen Paaprk LM		40.41 [0.000]	
Cragg-Donald Wald F		63.93 [16.38]	
Observations	510	540	540
R-squared	0.189	0.247	0.173

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values. Values in square brackets are *p*-values and values in curly brackets are critical values corresponding to the Stock Yogo test at the 10% level.

5.4. Robustness check

5.4.1. Replace explanatory variables

In the benchmark regression, we used the proportion of the total area of household contracted cultivated land transfer in each province to the total area of household contracted cultivated land. To further verify the robustness of our conclusions, we used the total area of household contracted cultivated land transfer (in millions of acres) as a substitute. The regression results are shown in column (1) of Table 6, and the replacement of land transfer still has an improving effect on agricultural green total factor productivity at the 1% level. The conclusion of this article is robust.

5.4.2. Changing the measurement of green total factor productivity in agriculture

Divergences in methodological approaches have led to substantial variation in the estimated values of agricultural GTFP. A key source of inconsistency lies in the estimation of agricultural capital stock, as different academic paradigms yield distinct calculation strategies, thereby compromising the reliability and comparability of GTFP outcomes. To mitigate potential biases arising from these discrepancies, this study employs original statistical indicators rather than derived GTFP indices to conduct regression analysis. Building upon the theoretical foundation of the Solow residual framework, this study restructures the empirical model by replacing the conventional GTFP index with the growth rate of value added in the primary sector as the dependent variable. Labor input is proxied by the growth rate of employment in the primary industry, while capital input is constructed as a composite metric comprising the growth rate of agricultural machinery utilization, expansion in sown area, and growth in fertilizer application—capturing capital input from multiple dimensions. To control for confounding effects, several auxiliary variables are introduced, including the share of government agricultural expenditure, the growth rate of the rural population with higher education, per capita GDP, and unit agricultural output value. These variables reflect broader socio-economic and policy dimensions that may influence productivity dynamics. The regression results, shown in column (2) of Table 6, indicate that the core findings remain statistically robust even when the measurement of agricultural GTFP is modified. This reinforces the validity and robustness of the study's conclusions and demonstrates the effectiveness of the alternative measurement strategy in addressing methodological inconsistencies.

5.4.3. Explanatory variables lagged by one period

Due to the inherently long production cycle in agriculture, land transfer typically triggers subsequent adjustments in cropping structure and the adoption of advanced technologies—such as the selection of appropriate machinery and high-quality seeds—whose productivity effects often manifest over multiple years. For instance, the acquisition of large-scale agricultural machinery following land consolidation generally occurs towards the end of the year, while its contribution to efficiency improvements becomes evident in the following production cycle. To empirically

Table 6. Robustness test

Variables	(1)	(2)	(3)	(4)	(5)
	tfp	tfp1	tfp	tfp	tfp
fd1	0.002***				
	(3.52)				
fd		0.464***		0.159***	0.227***
		(6.325)		(3.680)	(3.628)
L.fd			0.163***		
			(3.267)		
gdp	–1.14e-06	–4.07e-06***	–1.19e-06**	–1.10e-06***	–1.31e-06***
	(–2.52)	(–5.987)	(–2.573)	(–2.847)	(–2.805)
rpo	–0.546***	0.252	–0.506***	–0.442***	–0.443***
	(–4.25)	(1.326)	(–3.925)	(–4.001)	(–3.137)
wag	0.128	–0.212	0.130	0.125	0.133
	(1.02)	(–1.473)	(1.349)	(1.506)	(1.060)
dag	0.072	0.311	0.0187	–0.0907	–0.0309
	(0.43)	(1.255)	(0.116)	(–0.639)	(–0.184)
med	0.025	–0.190***	0.0207	0.0219	0.0210
	(0.57)	(–3.201)	(0.531)	(0.647)	(0.459)
psi	1.068***	–1.362***	1.279***	1.141***	1.226***
	(3.98)	(–3.557)	(4.683)	(5.196)	(4.646)
individual fixed effect	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	–12.40**	1.134***	1.019***	1.008***	0.985***
	(–2.577)	(8.718)	(11.58)	(13.29)	(9.493)
Observations	540	540	510	540	468
R-squared	0.720	0.506	0.163	0.185	0.183
Number of id	30	30	30	30	26

Note: *** and ** indicate significance at the 1% and 5% levels, respectively. The values in parentheses are *t*-values.

assess the delayed effects of land transfer on agricultural green total factor productivity (AGTFP), this study introduces a one-period lag of the land transfer variable in the regression analysis. As reported in column (3) of Table 6, the coefficient remains significantly positive at the 1% level, indicating that even lagged land transfer exerts a favorable influence on AGTFP. These findings reinforce the robustness of the study's core conclusions.

5.4.4. Shrinkage regression

To mitigate the potential influence of outliers—arising from measurement inaccuracies, data entry errors, or genuine extreme observations—which may substantially skew key statistical metrics such as the mean and variance and distort the overall distribution, this study applies a 1% winsorization to all continuous variables. The corresponding regression outcomes are presented in column (4) of Table 6. The estimated coefficients for land transfer remain statistically significant at the 1% level, suggesting that the relationship between land transfer and AGTFP is robust to the presence of extreme values.

5.4.5. Excluding municipalities

Beijing, Tianjin, Shanghai, and Chongqing—China's four centrally administered municipalities—are markedly more economically developed than other provincial-level regions, often exhibiting substantially higher values in key indicators such as GDP per capita and urbanization rate. While these observations may not formally qualify as statistical outliers, their inclusion in the analysis may introduce heteroskedasticity or non-linear effects, thereby complicating the interpretation of regression estimates. Given their disproportionate weight in terms of economic output, population size, and other macro-level characteristics, these municipalities may exert undue influence on estimation results (e.g., through leverage effects). To address this concern, a robustness check is performed by excluding the four municipalities from the sample. The regression results, reported in column (5) of Table 6, confirm that the effect of land transfer on agricultural green total factor productivity remains statistically significant at the 1% level, affirming the robustness of the core findings.

5.5. Mechanism analysis

The subsequent analysis investigates the mediating roles of three potential transmission channels: the scale effect, rural labor reallocation, and structural optimization. Specifically, land transfer may exert an influence on AGTFP through these intermediary mechanisms, each representing a distinct pathway through which efficiency gains can be realized.

5.5.1. Scale effect

Table 7 presents the empirical results of the mechanism analysis related to the scale effect. As shown in column (1), land transfer exerts a significantly positive impact on the scale effect at the 5% level, suggesting that land reallocation enhances operational scale in agriculture. Column (2) reports the regression results after simultaneously including both land transfer and the scale effect in the model. The coefficients for both variables remain significantly positive, indicating that land transfer contributes to improvements in AGTFP by facilitating scale expansion.

The underlying mechanisms can be understood as follows: land transfer promotes AGTFP through scale-enhancing channels characterized by multiple dimensions. First, by enabling the transition from fragmented smallholder farming to moderately scaled operations, land transfer alleviates inefficiencies such as land abandonment and fragmentation. This transition promotes more intensive use of arable land and improves scale efficiency. Second, land consolidation fosters the emergence of new agricultural management entities, who, through accumulated production and managerial experience, engage in specialized and expanded operations, thereby enhancing overall productivity.

Moreover, scaled-up operations create favorable conditions for technology adoption and cost control. Larger-scale farms are more likely to adopt advanced agricultural

Table 7. Mechanistic tests of scale effects

Variables	(1)	(2)
	sca	tfp
fd	1.245***	0.146*
	(3.257)	(1.743)
sca		0.0577**
		(2.201)
gdp	−2.77e-06	−9.86e-07*
	(−0.914)	(−1.965)
rpo	−6.906***	−0.112
	(−16.98)	(−0.444)
wag	0.666	0.0805
	(1.386)	(0.620)
sap		−0.0104
		(−0.287)
dag	0.187	−0.0962
	(0.882)	(−0.711)
med	0.457*	−0.00591
	(1.972)	(−0.172)
psi	2.429	1.199**
	(1.680)	(2.411)
individual fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Constant	8.989***	0.522*
	(18.64)	(1.707)
Observations	510	510
R-squared	0.905	0.171
Number of id	30	30

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values.

technologies and mechanized equipment, which help reduce the input intensity of chemical fertilizers per unit of land. In addition, scale expansion lowers the per-unit fixed cost of sustainable practices such as conservation tillage, making their adoption economically viable. These dynamics collectively improve factor allocation efficiency, mitigate non-point source pollution, and foster a shift toward resource-efficient and environmentally sustainable agricultural practices—thereby enabling the long-term enhancement of green total factor productivity in agriculture.

5.5.2. Labor force mobility

Table 8 reports the results of the mechanism analysis concerning rural labor mobility. In column (1), the regression coefficient of land transfer on labor mobility is significantly positive at the 1% level, indicating that land transfer facilitates the reallocation of rural labor. Column (2) incorporates both land transfer and labor mobility into the regression model, with both variables maintaining statistically significant and positive coefficients. These findings suggest that land transfer contributes to the enhancement of AGTFP by promoting labor mobility.

The mechanism underlying this relationship can be interpreted as follows. First, land transfer alleviates the rigid linkage between rural labor and land inherent in the traditional smallholder economy. As farmland is consolidated under new, more efficient management entities, older or less productive laborers are substituted, enabling surplus labor to transition toward non-agricultural employment sectors. This facilitates a beneficial cycle of "factor reallocation–efficiency improvement." Furthermore, migrant labor serves as a conduit for technological spillover: returning rural workers often bring back advanced agricultural techniques and managerial practices acquired in urban settings. This supports the diffusion of green technologies such as soil testing and formula fertilization, as well as precision pest and disease control. Second, labor mobility contributes to the accumulation of agricultural human capital through experiential learning. Non-farm employment exposes rural workers to skill development and training opportunities, which, upon return, are reinvested into agricultural production. This enhances innovation capacity in environmentally sustainable farming practices, further supporting the long-term improvement of AGTFP.

Table 8. Mechanistic tests of labor mobility

Variables	(1)	(2)
	lab	tfp2
fd	0.710***	0.187***
	(9.081)	(3.456)
lab		0.0459*
		(–1.57)
gdp	3.01e-06***	–1.02e-06**
	(4.178)	(–2.180)
rpo	–0.381*	–0.530***
	(–1.890)	(–4.107)
wag	0.117	0.129
	(0.776)	(1.345)
dag	0.200	–0.0147
	(0.790)	(–0.0911)
med	0.288***	0.0321
	(4.716)	(0.804)
psi	0.127	1.339***
	(0.298)	(4.928)
individual fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Constant	0.214	1.028***
	(1.543)	(11.59)
Observations	510	510
R-squared	0.599	0.165
Number of id	30	30

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values.

5.5.3. Capital deepening

Table 9 presents the results of the mechanism analysis concerning structural upgrading via capital deepening. Column (1) reports that land transfer has a significantly positive effect on capital deepening at the 1% level, indicating that land consolidation contributes to increased capital intensity in agricultural production. In column (2), after jointly including land transfer and capital deepening in the regression model, both coefficients remain significantly positive, confirming that capital deepening serves as a mediating channel through which land transfer enhances AGTFP.

The underlying mechanism can be explained as follows. First, land transfer helps dismantle the fragmented landholding patterns characteristic of the traditional smallholder system by reallocating land toward more efficient, large-scale agricultural entities. This reorganization increases the demand for scaled operations, which incentivizes these entities to intensify capital investment. Capital deepening, in turn, alleviates constraints on technological adoption, enabling larger farms to implement capital-intensive and environmentally friendly innovations, such as precision agriculture systems and advanced biological breeding technologies. Second, increased capital input fosters the upgrading of agricultural infrastructure, creating positive externalities across production networks. For instance, investment in efficient water-saving irrigation technologies enhances both productivity and resource conservation by optimizing water allocation and mitigating groundwater depletion. Similarly, the development of cold-chain logistics infrastructure reduces post-harvest losses, thereby improving the conversion of inputs into effective agricultural output. Moreover, capital deepening promotes more efficient factor allocation through the substitution effect: in the context of increased capital availability, production systems increasingly replace labor and resource-intensive practices with capital-based inputs, reducing environmental pressure and enhancing sustainable productivity growth in agriculture.

Table 9. Mechanistic tests of structural effects

Variables	(1)	(2)
	lzj	tfp
fd	0.118**	0.159***
	(2.047)	(3.171)
lzj		1.325***
		(4.842)
gdp	–4.78e-06***	–1.23e-06**
	(–5.696)	(–2.386)
rpo	–0.843***	–0.530***
	(–3.657)	(–3.916)
wag	0.0971	0.126
	(0.430)	(1.310)
dag	2.807***	0.0282
	(5.500)	(0.133)
med	0.239**	0.0245
	(2.298)	(0.601)
psi	–0.529	0.0183
	(–1.193)	(0.374)
individual fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Constant	0.285*	1.025***
	(1.884)	(11.41)
Observations	510	510
R-squared	0.577	0.162
Number of id	30	30

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values.

5.5.4. Common and synergistic effects

In the previous text, we examined the single effect of scale effect, labor mobility, and capital deepening on the relationship between land transfer and agricultural green total factor productivity. To further test whether there is a common effect among these three channels, we introduced three mechanism variables into the model. The test results are shown in column (1) of Table 10. From the results, it can be seen that the scale effect and labor mobility are significantly positive at the 5% and 1% levels, respectively, while the capital deepening coefficient is positive but not significant. The reason for this result may be that in the short term, the increase in agricultural green total factor productivity promoted by land transfer may rely more on economies of scale and labor mobility, while capital deepening may require longer time or appropriate conditions to show its effects. At the same time, this also suggests that policy design needs to be tailored to local conditions, focusing on the specific contributions and implementation paths of various factors in practice, in order to maximize the actual benefits of land transfer.

To further test whether there is a synergistic effect between these three channels, we interacted the three mechanism variables pairwise. The test results are shown in column (1) of Table 10. From the results, the coefficients of sca×lab, sca×lzj, lab×lzj are significantly positive at the 10%, 1%, and 1% levels, respectively, indicating a synergistic effect between the mechanism variables. The significant results of the interaction term between scale effect, labor mobility, and capital deepening indicate that there is a synergistic effect between different mechanism variables, which means that when they work together, they can produce better results than the independent effects of any single factor. This synergistic effect is extremely important in policy design and practice, reminding policymakers to comprehensively consider the complementary nature of various channels and their joint application when promoting land transfer to improve agricultural productivity, in order to ensure the maximization of agricultural production efficiency. This also emphasizes that farmers and related agricultural economic entities should pay attention to mutual assistance, cooperation, and resource integration when expanding their business scale, optimizing labor force, and investing capital, in order to fully leverage the advantages of agricultural modernization.

5.6. Heterogeneity analysis

To investigate the heterogeneous impacts of land transfer on AGTFP, this study employs a grouped regression framework across three dimensions: geographic location, agricultural production function, and production type. Regional heterogeneity: While land transfer generally exhibits a significant positive effect on AGTFP, its magnitude and direction may vary across regions due to disparities in natural resource endowment, agricultural practices, and levels of economic development. Following the regional classification standard of the National Bureau of Statistics, the sample is segmented into eastern, central, and western regions to conduct subgroup analyses. Functional heterogeneity of agricultural zones: In line with the functional delineation outlined in the Medium- and Long-Term Plan for National Food Security (2008–2020), the sample is further categorized into major grain-producing areas, key grain-consuming (marketing) regions, and balanced zones (areas with relatively even production and consumption). This allows the study to assess whether the role of land transfer differs across functionally distinct agricultural zones. Heterogeneity by agricultural production type: Finally, the analysis distinguishes between crop farming and livestock-dominated regions to examine whether the effect of land transfer on AGTFP is contingent on the dominant agricultural activity.

5.6.1. Geographic location

The regression results in columns (1) to (3) of Table 11 show that in the eastern and central regions, land transfer still has a significant promoting effect on agricultural green total factor productivity, with coefficient values being positive at the 5% significance level; However, the significance test in the western region did not pass. Possible reasons include: firstly, the uncertainty of land ownership. The western

Table 10. Synergistic effect test of mechanism variables

Variables	(1)	(2)	(3)	(4)
	tfp	tfp	tfp	tfp
fd	0.183***	0.171***	0.155***	0.191***
	(3.359)	(3.147)	(3.014)	(3.481)
sca	0.0665**	0.0685**	0.0661**	
	(2.408)	(2.438)	(2.373)	
lab	0.172***	0.0437		–0.0431
	(3.17)	(0.410)		(–1.388)
lzj	0.0435		0.0970	–0.0265
	(0.880)		(0.373)	(–0.302)
sca×lab		0.062*		
		(2.02)		
sca×lzj			1.208***	
			(4.27)	
lab×lzj				0.0139***
				(4.21)
gdp	–1.03e-06**	–6.81e-07	–1.22e-06**	–1.14e-06**
	(–1.982)	(–1.339)	(–2.250)	(–2.174)
rpo	–0.110	–0.155	–0.104	–0.552***
	(–0.480)	(–0.651)	(–0.456)	(–4.052)
wag	0.0900	0.119	0.0739	0.132
	(0.923)	(1.142)	(0.738)	(1.347)
dag	0.0255	–0.0899	0.0304	0.0578
	(0.120)	(–0.546)	(0.136)	(0.271)
med	0.0136	0.00478	0.00457	0.0387
	(0.316)	(0.115)	(0.105)	(0.923)
psi	1.156***	1.185***	1.153***	1.326***
	(4.114)	(4.252)	(4.093)	(4.840)
individual fixed effect	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes
Constant	0.444*	0.442*	0.444*	1.036***
	(1.699)	(1.688)	(1.693)	(11.48)
Observations	510	510	510	510
R-squared	0.176	0.176	0.172	0.166
Number of id	30	30	30	30

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values.

region often involves more collective land ownership or forest and grassland management, resulting in a less complete legal and institutional foundation for land transfer compared to the eastern and central regions. This uncertainty limits the breadth and depth of land transfer, making farmers face higher risks and constraints when transferring or leasing land, and inhibiting the potential productivity improvement of land transfer. Secondly, market transaction costs are high. Geographical factors and other factors result in higher transaction costs in the western market. The remote geographical location limits the openness of the market, leading to increased transaction costs, which makes land transfer difficult to implement or hindered, thereby affecting the ability of these areas to achieve agricultural productivity improvement through land transfer. Thirdly, there are differences in agricultural structure. The agricultural structure in the western region is different from that in the eastern and central regions, with a larger proportion of non land intensive industries such as animal husbandry. This different agricultural structure means that the relationship between productivity and land transfer is not direct, and agricultural activities in a region may rely more on other resources such as grasslands and feed, so the impact of land transfer is relatively small.

5.6.2. Agricultural production function

As shown in columns (1) to (3) of Table 12, land transfer exhibits a statistically significant positive effect on AGTFP in major grain-producing regions, with coefficients significant at the 1% level. In contrast, the coefficients for the

Table 11. Heterogeneity test for geographic location

Variables	(1)	(2)	(3)
	tfp	tfp	tfp
fd	0.143**	0.0874*	–0.102
	(2.183)	(1.858)	(–0.619)
gdp	–1.15e-06**	1.13e-06	–4.84e-06**
	(–1.977)	(1.529)	(–2.121)
rpo	–0.750***	0.229*	–1.068***
	(–2.853)	(1.873)	(–3.577)
wag	0.206	–0.0235	–0.0164
	(1.614)	(–0.269)	(–0.0693)
dag	0.0283	0.000341	0.357
	(0.115)	(0.00231)	(1.065)
med	0.0360	–0.108***	–0.141
	(0.732)	(–4.739)	(–0.808)
psi	1.879***	–0.438*	–0.944
	(4.992)	(–1.664)	(–1.131)
individual fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Constant	0.977***	0.989***	1.844***
	(8.159)	(10.68)	(6.222)
Observations	221	102	187
R-squared	0.263	0.444	0.154
Number of id	13	6	11

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are *t*-values.

Table 12. Heterogeneity test for agricultural production functions

Variables	(1)	(2)	(3)
	tfp	tfp	tfp
fd	0.256***	0.0241	-0.0458
	(2.783)	(0.894)	(–0.238)
gdp	–2.31e-07	–1.96e-07	–7.40e-06**
	(–0.254)	(–0.808)	(–2.462)
rpo	–0.326	–0.301**	–0.974***
	(–0.962)	(–2.406)	(–3.012)
wag	0.279	0.0559	–0.0576
	(1.573)	(1.132)	(–0.237)
dag	0.0214	0.0533	0.133
	(0.0866)	(0.361)	(0.395)
med	–0.0676	0.00210	0.0231
	(–0.934)	(0.122)	(0.223)
psi	1.722***	0.340	–0.782
	(4.857)	(1.021)	(–0.868)
individual fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Constant	0.792***	1.045***	1.740***
	(3.914)	(27.44)	(5.993)
Observations	221	119	170
R-squared	0.256	0.137	0.157
Number of id	13	7	10

Note: *** and ** indicate significance at the 1% and 5% levels, respectively. The values in parentheses are *t*-values.

major grain marketing areas and the balanced production-marketing regions are statistically insignificant, suggesting that the effect of land transfer on AGTFP is more pronounced in areas primarily responsible for grain production. Possible reasons are: firstly, the main grain producing areas have vast arable land and natural conditions suitable for large-scale mechanized operations. Land transfer in such areas can effectively promote large-scale production, and farmers can enjoy economies of scale by concentrating more land for large-scale cultivation. Large scale operation can reduce unit production costs, improve resource utilization efficiency, and significantly enhance productivity. Secondly, the main grain producing areas are important regions for grain production, and land transfer may encourage farmers to expand their agricultural production scale and introduce more production factors to meet market demand. This expansion and intensification of production methods may lead to improved production efficiency. Land transfer can encourage farmers to optimize the supply chain and logistics of agricultural products, reduce energy consumption and carbon emissions caused by product loss, storage, and transportation, and thus promote the improvement of agricultural green total element productivity.

5.6.3. Objects of agricultural production

The first column of Table 13 shows that the coefficient of land transfer in the planting area is positive at a significance level of 1%, indicating that land transfer has a positive effect on the agricultural green total factor productivity in the planting area. Column (2) of Table 13 shows that the coefficient of land transfer in the livestock area is not significant, indicating that land transfer has no significant impact on the agricultural green total factor productivity of the livestock area. The reason for this difference is that land circulation in planting areas increases land concentration, which helps to achieve large-scale operations. Through scaling up, farmers can more effectively utilize modern agricultural technologies such as precision irrigation and mechanized operations. This technology promotion not only improves labor productivity, but also reduces production costs per unit area, making resource allocation more efficient. In the planting area, land transfer promotes the promotion and application of modern agricultural technologies (such as precision irrigation and mechanized operations) through large-scale management, reduces production costs per unit area, and improves factor allocation efficiency; In animal husbandry areas, animal husbandry areas are important areas for animal husbandry production, involving the supply chain and processing links of livestock products. Land transfer may encourage farmers to expand the scale of animal husbandry production and increase the density of livestock and poultry breeding. This expansion and increase in density may lead to increased emissions of livestock manure and energy consumption during feed production, reducing agricultural green total factor productivity.

Table 13. Heterogeneity test of agricultural production objects

Variables	(1)	(2)
	tfp	tfp
fd	0.178***	0.0238
	(3.424)	(0.179)
gdp	–6.10e-07	–9.65e-07
	(–0.914)	(–1.270)
rpo	–0.432**	–0.760***
	(–2.143)	(–3.320)
wag	0.251**	–0.135
	(2.317)	(–0.664)
dag	–0.0544	0.354
	(–0.266)	(1.238)
med	0.00229	–0.167
	(0.0553)	(–1.353)
psi	1.626***	–0.197
	(5.628)	(–0.280)
individual fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Constant	0.886***	1.598***
	(7.785)	(6.569)
Observations	289	221
R-squared	0.241	0.131
Number of id	17	13

Note: *** and ** indicate significance at the 1% and 5% levels, respectively. The values in parentheses are *t*-values.

6. Conclusions and recommendations

6.1. Conclusions

This article analyzes the provincial panel data of 30 provinces (including autonomous regions and municipalities) in China from 2005 to 2022 from the perspective of agricultural green total factor productivity. By using a fixed effects model, this article empirically studies the impact of agricultural land transfer on agricultural green total factor productivity, and deeply analyzes its impact mechanism and heterogeneity characteristics. Research has found that firstly, agricultural land transfer has a significant promoting effect on agricultural green total factor productivity, and even after endogeneity and robustness tests, this conclusion remains robust. Secondly, from the perspective of mechanism analysis, land transfer has improved the green total factor productivity of agriculture by expanding the scale effect of agriculture, accelerating the transfer of rural labor, and promoting capital deepening. And it has a synergistic effect. Thirdly, heterogeneity analysis shows that agricultural land transfer has a particularly significant effect on enhancing agricultural green total factor productivity in the eastern and central regions, major grain producing areas, and planting areas. According to these research findings, China should accelerate the pace of agricultural land transfer in order to steadily improve agricultural green total factor productivity.

6.2. Policy recommendations

(1) Accelerating rural land market development to facilitate agricultural land transfer. In recent years, the level of agricultural land transfer in China has remained at around 40%, seriously affecting the improvement of agricultural production efficiency and green agricultural production. We should comprehensively promote the transfer of agricultural land by strengthening the construction of rural land trading markets, improving land dispute and regulation mechanisms, and enhancing support for large-scale farmers, fully leveraging the promoting effect of agricultural land transfer on agricultural green total factor productivity. Once again, promote innovation in agricultural production and management, and enhance technological efficiency. The transfer of agricultural land should adhere to the concept of moderate scale management, innovate agricultural management models, optimize the allocation of agricultural production factors, and thereby enhance the green total factor productivity of agriculture. At the same time, we should be vigilant against the decline in management efficiency caused by excessive expansion of production scale, avoid the phenomenon of "diseconomies of scale" caused by rising production costs, and prevent the deterioration of technical efficiency. In addition, in the allocation of agricultural production factors, the fundamental regulatory role of the market should be fully utilized, and land transfer should be orderly promoted through scientific guidance, highlighting the positive impact of land transfer on technological efficiency improvement.

(2) Economies of scale, labor mobility, and capital deepening are important mechanisms for improving agricultural green total factor productivity. Firstly, various provinces and cities encourage land transfer through policy regulation and market guidance to achieve large-scale operations. Policies can support the expansion of agricultural operations through models such as land shareholding, land intensification, and large-scale cooperative societies. For example, the government provides low interest loans and tax reductions to encourage farmers or new agricultural operators to expand their business scale. Secondly, policies can focus on providing financial credit support for new agricultural entities expanding their production scale. This may include establishing specialized Agricultural Development Bank loans, providing low interest agricultural equipment purchase loans or credit guarantee projects to alleviate the initial capital investment pressure on farmers and promote the rapid introduction and application of agricultural technology. Finally, establish a more comprehensive vocational training system and carry out specialized training programs for modern agricultural technology to improve the skill level of rural labor. This not only promotes labor mobility, but also enhances the production capacity of left behind labor.

(3) The transfer of agricultural land has heterogeneous impacts on the green total factor productivity of agriculture in different regions. Therefore, we should implement different policies according to local conditions. Firstly, in major grain producing areas, land transfer significantly promotes agricultural green total factor productivity. Therefore, promoting moderate scale operation is key. On the one hand, promoting centralized land circulation through policy guidance can achieve economies of scale in agricultural production, while on the other hand, avoiding excessive resource concentration caused by excessive scaling. Secondly, in the eastern region, we will continue to support the technological development and innovation projects of leading agricultural enterprises, and guide the flow of resources and markets towards efficient areas. In the central region, a special technology support fund will be established to assist small and medium-sized enterprises and farmers in technological innovation. In the western region, the focus is on investing in infrastructure construction and ecological environment protection funds to improve land use efficiency and reduce environmental burden. Finally, the planting area shows a significant increase in agricultural green total factor productivity through land transfer, especially through the promotion of modern agricultural technology. Policies should focus on supporting the promotion and application of precision agriculture technology and facilities. For example, conducting technical training programs to promote advanced planting technologies such as precision irrigation and intelligent planting.

Data availability statement

Data are mainly from China Statistical Yearbook (https://www.stats.gov.cn/sj/ndsj/); China Tertiary Industry Statistical Yearbook (https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_ 1907806.html)and the China Rural Statistics Yearbook (https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1907997.html). It was used to support the findings of this study are available from the corresponding author upon request.

Conflicts of interest

The author declares that he has no conflict of interest.

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