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Regional Disparities, Distributional Dynamics, and Spatial Convergence of Biased Technological Change in Chinese Agriculture Under Land Constraints

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Abstract

Under increasing land constraints and food security pressures, understanding the direction of agricultural technological change is essential for improving land use efficiency. This study investigates the regional disparities, distributional dynamics, and spatial convergence of biased technological change in Chinese agriculture. Dagum Gini decomposition is used to identify regional differences and their sources, kernel density estimation examines distributional dynamics, and spatial econometric models test convergence patterns. The results show that agricultural technological progress in China is predominantly biased toward labor and capital, with labor–land bias being the strongest and continuously increasing. This indicates a gradual shift from land-dependent growth toward more intensive use of non-land inputs under farmland constraints. Regional disparities in technological bias have widened over time, mainly driven by interregional differences and distributional overlap. Kernel density analysis reveals dynamic but largely non-polarized evolution, suggesting gradual adjustment rather than structural divergence. Although no σ-convergence is observed, both absolute and conditional β-convergence exist, with faster convergence in the labor–land dimension and under conditional settings. These findings imply that regions tend to adapt to land constraints through differentiated technological pathways, resulting in uneven improvements in land-related productivity. Overall, biased technological change plays an important role in shaping land use efficiency under resource constraints. The study provides evidence for understanding agricultural adaptation to land scarcity and offers implications for sustainable agricultural development, farmland protection, and long-term food security.

Keywords: biased technological change; land use efficiency; farmland constraints; regional disparities; spatial convergence; food security

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1. Introduction

Ensuring food security while protecting limited farmland resources has become one of the most pressing challenges for sustainable agricultural development worldwide. Population growth, urban expansion, ecological degradation, and climate change have intensified pressure on agricultural land systems, making improvements in land use efficiency increasingly critical [1]. Under these constraints, expanding cultivated land is no longer a feasible long-term strategy for many countries. Instead, sustaining agricultural production increasingly depends on improving productivity within existing land resources. Consequently, understanding how agricultural systems adapt to land constraints has become central to discussions on farmland protection, sustainable intensification, and long-term food security.

China provides a particularly important context for examining these issues. As the world's largest agricultural producer, China feeds nearly one-fifth of the global population with less than 9% of the world's arable land[1]. Despite remarkable growth in agricultural output, Chinese agriculture faces increasing pressure from shrinking cultivated land, labor outmigration driven by urbanization, ecological constraints, and rising production costs. Meanwhile, strict farmland protection policies, such as the "1.8 billion mu red line", have further reduced the possibility of expanding cultivated land[2]. Under these circumstances, sustaining agricultural growth increasingly relies on improving factor productivity and optimizing production patterns rather than increasing land inputs. Therefore, understanding how agricultural technology evolves under land constraints is crucial for improving land-related productivity and maintaining food security.

Previous studies have extensively examined agricultural adaptation under resource constraints, mainly focusing on technological efficiency, productivity change, agricultural innovation, and land use performance [2–7]. Methods such as Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), Malmquist indices, and growth accounting approaches have been widely used to evaluate agricultural technological progress and efficiency dynamics [8–10]. Studies on land use efficiency similarly emphasize the importance of infrastructure conditions, resource allocation, urbanization, and institutional arrangements in shaping agricultural performance [7,11]. International evidence further suggests that differences in resource endowments often induce heterogeneous technological pathways and unequal agricultural outcomes across regions [12,13].

Existing international research increasingly recognizes that agricultural technological development is closely related to land scarcity and factor endowments. The induced innovation perspective proposed by Ruttan and Hayami [12] suggests that differences in land and labor constraints lead to distinct technological trajectories, with land-scarce economies tending to develop land-saving technologies. Subsequent studies show that mismatches between technological pathways and local resource conditions often reduce agricultural efficiency and constrain sustainable growth [14–16]. These findings imply that agricultural technological choices are not neutral but evolve alongside resource constraints and changing factor scarcity. Similarly, directed technological change theory argues that changes in relative factor scarcity alter innovation incentives and induce differentiated technological pathways [17,18].

Although previous studies provide important insights, several limitations remain. First, insufficient attention has been paid to the direction of agricultural technological change under land constraints. Existing studies mainly evaluate agricultural development through overall productivity growth or efficiency improvement, while relatively limited attention has been devoted to whether increasing land scarcity reshapes technology direction choices in agriculture. Yet land constraints may alter relative factor productivity and induce differentiated improvements in labor-, capital-, and land-related efficiency, thereby influencing long-term agricultural adaptation pathways [17]. Existing studies on biased technological change mainly focus on industrial sectors or economic growth and often employ CES production functions, frontier methods, or factor income shares to identify technological bias [8,9,19]. Applications in agriculture remain limited, especially when land is incorporated explicitly as a constrained factor.

Second, limited attention has been given to regional heterogeneity in agricultural technological bias under land constraints. Existing research has widely examined regional disparities in agricultural productivity, efficiency, and innovation [20]. However, relatively few studies investigate whether technology direction choices differ across regions facing heterogeneous land constraints and factor endowments, or how such differences evolve over time. Given substantial regional variations in economic development, infrastructure conditions, labor mobility, and resource scarcity, agricultural technological pathways are unlikely to evolve uniformly [17,21].

Third, research on the spatio-temporal evolution of agricultural technological bias under land constraints remains limited. Previous studies commonly apply inequality decomposition or convergence analysis to agricultural productivity and efficiency, but these methods are often used separately and focus on overall technological levels. For example, Theil indices and conventional Gini coefficients are frequently used to measure regional inequality [22], while σ-convergence and β-convergence models are employed to examine convergence in technological innovation or efficiency [22,23]. In the context of agricultural technological bias, relatively little attention has been paid to simultaneously examining regional disparities, dynamic distributional evolution, and spatial convergence within a unified analytical framework. As a result, understanding of the long-term evolution of agricultural technology direction choices and associated land-related productivity remains incomplete.

These gaps are particularly important in China, where substantial regional differences in resource endowments coexist with increasing farmland pressure and rapid structural transformation. Against this background, several questions remain unresolved. Do agricultural technology direction choices exhibit significant regional heterogeneity under land constraints? How have such differences evolved over time? Do they persist, or gradually converge? More importantly, what do these processes reveal about long-term agricultural adaptation and land-related productivity under food security pressure?

To address these questions, this study investigates the regional disparities, distributional dynamics, and spatial convergence of biased technological change in Chinese agriculture under land constraints. Specifically, a multi-factor CES production framework incorporating land, labor, and capital is employed to characterize agricultural technological bias [24]. Dagum Gini coefficient decomposition is used to identify regional disparities and their sources [22]; kernel density estimation is applied to reveal dynamic distributional evolution [25]; and spatial convergence models are constructed to examine long-term convergence patterns [23].

Compared with existing studies, this paper contributes in three aspects. First, this study shifts attention from the level of agricultural technological progress to the direction of technological change under land constraints. Existing studies mainly evaluate agricultural development through productivity growth, efficiency improvement, or innovation performance, while relatively little attention has been paid to how increasing land scarcity and farmland protection pressures reshape technology direction choices in agriculture. By explicitly incorporating land into a multi-factor framework of biased technological change, this study captures differentiated changes in capital-, labor-, and land-related productivity, thereby providing a new perspective for understanding how agricultural systems improve land use efficiency and adapt to constrained farmland resources.

Second, this study extends the analysis of agricultural technological change from static evaluation to the spatio-temporal evolution of technological bias. Rather than treating biased technological change as a fixed characteristic, this paper examines whether technology direction choices exhibit persistent regional heterogeneity under land constraints, how these differences evolve over time, and whether they eventually converge. This perspective helps explain long-term regional differences in land-related productivity and reveals how agricultural systems adapt to heterogeneous resource endowments and farmland scarcity.

Third, this study develops an integrated analytical framework linking the measurement of biased technological change with regional disparity decomposition, distributional dynamics, and spatial convergence. Specifically, a multi-factor CES production framework, Dagum Gini decomposition, kernel density estimation, and dynamic spatial convergence models are combined to trace the complete evolution process of agricultural technological bias—from differentiated factor efficiency changes to regional disparities and long-term convergence patterns. Compared with previous studies that typically examine these dimensions separately, this framework provides a more systematic understanding of how technology direction choices shape the spatial evolution of land-related productivity under resource constraints.

Although the empirical analysis focuses on China, the findings have broader implications for countries facing similar challenges of farmland scarcity, labor reallocation, and agricultural transformation. As one of the world's largest agricultural producers operating under severe land constraints, China offers a representative case for understanding how agricultural systems maintain food security through differentiated technological pathways rather than farmland expansion.

2. Theoretical Analysis and Research Hypotheses

2.1. Land Constraints, Relative Factor Scarcity, and Biased Technological Change

Land is a fundamental input in agricultural production and a critical basis for ensuring food security. Under rapid urbanization, ecological protection requirements, and increasingly stringent farmland protection policies, cultivated land resources in China have become progressively constrained [26–28]. As opportunities for farmland expansion diminish, agricultural output growth increasingly depends on improvements in factor productivity rather than increases in cultivated land area.

According to directed technological change theory, technological progress is not neutral but responds to changes in relative factor scarcity and market incentives [17,18]. When land becomes relatively scarce or labor costs increase, agricultural production tends to adjust through changes in factor efficiency and relative marginal productivity. Such adjustments may induce technological progress to become biased toward specific production factors, thereby generating biased technological change [29].

Unlike neutral technological progress, biased technological change reflects differentiated improvements in the productivity of various production factors [30]. Therefore, the direction of technological change can be understood as the relative evolution of capital, labor, and land efficiency. Under increasing land constraints, technological progress is expected to become more biased toward non-land factors or toward improving land productivity through complementary inputs.

Hypothesis 1 (H1). *Under increasing land constraints, agricultural technological progress in China exhibits significant factor-biased characteristics, reflected in differentiated improvements in factor efficiency and relative marginal productivity.*

2.2. Regional Heterogeneity and Dynamic Evolution of Technological Bias

The direction of technological progress is closely associated with factor endowments, economic development levels, infrastructure conditions, and institutional environments [31–33]. Since these determinants differ substantially across regions, the evolution of factor efficiency and technological bias is unlikely to be homogeneous.

Compared with central and western China, eastern regions generally possess stronger capital accumulation capacity, higher innovation capability, and better agricultural infrastructure. These conditions facilitate differentiated improvements in factor productivity and may induce technological progress to evolve toward distinct directions [34]. By contrast, regions constrained by limited capital access or technological adoption may exhibit different patterns of technological bias.

Therefore, differences in regional factor endowments and development conditions are expected to generate persistent disparities in technological bias. Over time, changes in resource allocation and factor mobility may further reshape these differences, resulting in dynamic evolution in the distribution of technological bias.

Because technological bias fundamentally reflects differences in factor efficiency growth, regional disparities in biased technological change also imply heterogeneous adjustments in land-related productivity under resource constraints.

Hypothesis 2 (H2). *Significant regional disparities exist in agricultural technological progress bias, and these disparities evolve dynamically over time due to differences in factor endowments and development conditions.*

2.3. Spatial Interaction and Convergence of Biased Technological Change

Technological progress exhibits spatial dependence through channels such as knowledge spillovers, labor mobility, capital flows, and policy diffusion [35,36]. Increasing interactions across regions may facilitate the diffusion of agricultural technologies and gradually narrow differences in factor productivity.

Regions with lower levels of technological bias may improve relative factor efficiency by learning from more developed regions or adopting similar technological pathways [37]. Consequently, disparities in technological bias may diminish over time, leading to convergence in technology direction.

However, because structural conditions such as economic development, infrastructure, and industrial structure vary across regions, convergence is unlikely to occur toward a single uniform equilibrium [37]. Instead, technological bias is more likely to converge toward region-specific steady states.

Furthermore, convergence in technological bias implies gradual adjustment in regional differences in factor productivity, including productivity associated with land inputs. Spatial convergence therefore reflects not only similarity in technology direction but also long-term adaptation of agricultural production patterns under land constraints.

Hypothesis 3 (H3). *Agricultural technological progress bias exhibits spatial convergence characteristics, although convergence speeds differ according to local structural conditions.*

2.4. Theoretical Framework

The above analysis suggests that under land constraints, agricultural technological progress should be understood as a dynamic process driven by changes in relative factor scarcity and factor productivity. As cultivated land becomes increasingly constrained and labor mobility reshapes agricultural factor endowments, adjustments in relative factor prices and resource allocation lead to differentiated improvements in capital, labor, and land efficiency [18,38]. Such differentiated changes in factor efficiency are reflected in technological bias.

Because regions differ substantially in economic development, infrastructure conditions, and institutional environments, the direction and magnitude of technological bias are expected to exhibit regional heterogeneity and dynamic evolution [39]. At the same time, spatial interactions—including technology diffusion and factor mobility—may gradually reduce differences in technological bias and generate convergence patterns.

Therefore, this study argues that regional disparities, distributional dynamics, and spatial convergence in agricultural technological bias are fundamentally linked to long-term adjustments in relative factor productivity under land constraints. Examining these processes helps to reveal how agricultural production adapts to resource scarcity and provides new insights into balancing agricultural development and food security.

Based on the above theoretical analysis and hypotheses, Figure 1 illustrates the conceptual framework linking land constraints, factor efficiency adjustment, biased technological change, and the resulting regional disparities and spatial convergence patterns.

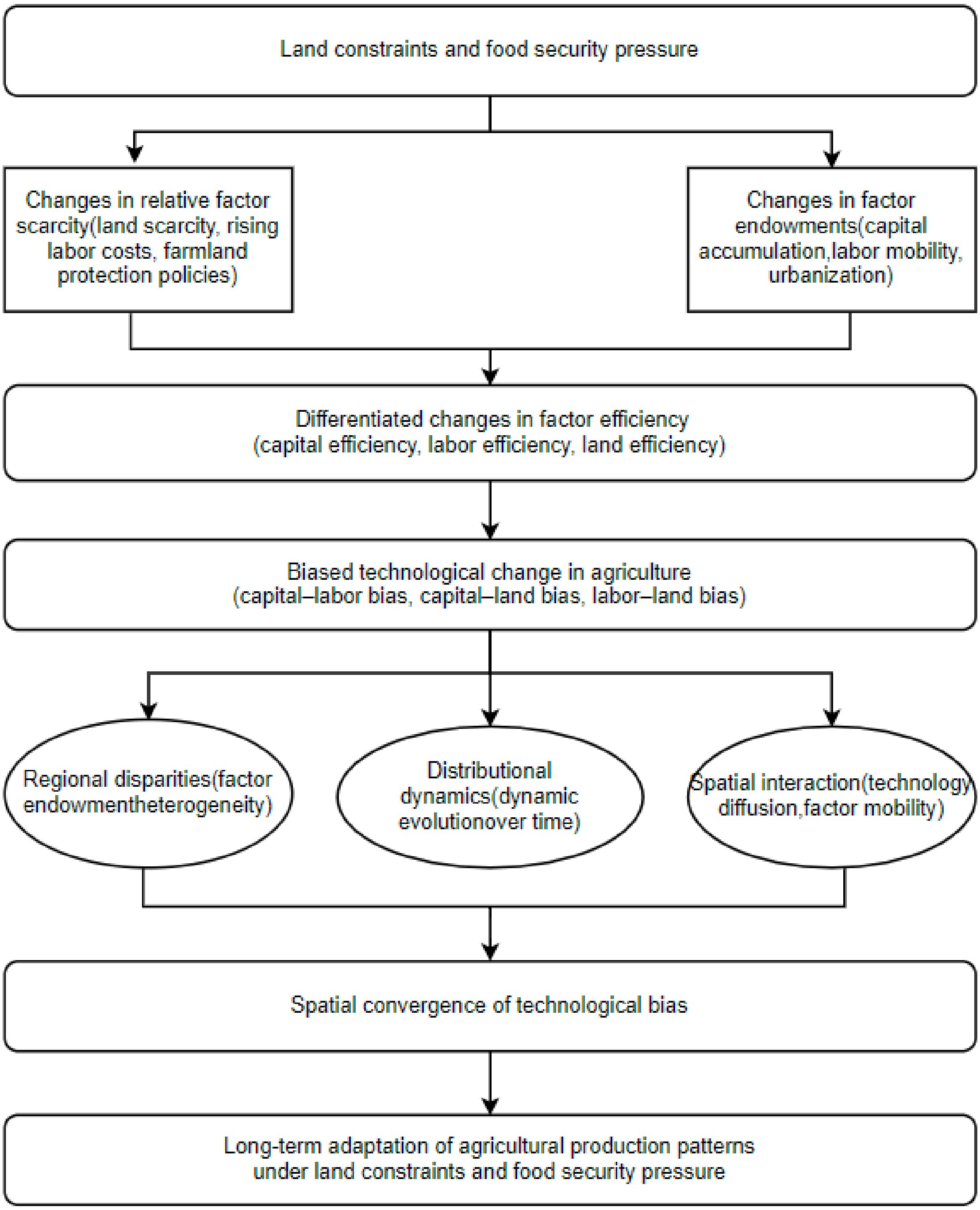

Figure 1. Theoretical framework of biased technological change under land constraints.

3. Research Methods and Data Sources

3.1. Measuring the Direction of Technological Change

3.1.1. Baseline Model for Measuring Technological Direction

To jointly capture both neutral and biased technological change, this paper specifies a general factor-augmenting production function in which capital, labor, and land are each augmented by factor-specific technologies. Let Γ_t^K, Γ_t^L and Γ_t^C denote the efficiency levels of capital, labor, and land, respectively.

The responsiveness of the ratio of marginal products between any two factors i and j with respect to their relative efficiency can be expressed as

$$Mar'_{ij} = \frac{\partial Mar_{ij}}{\partial\left(\Gamma_t^i/\Gamma_t^j\right)} \cdot \frac{d\left(\Gamma_t^i/\Gamma_t^j\right)}{dt} \quad (1)$$

where the corresponding term captures the extent to which technological change alters the relative marginal productivity of the two factors. Since biased technological change affects factor efficiencies and marginal products asymmetrically, the bias index is defined as

$$Bias_t^{ij} = \frac{Mar'_{ij}}{Mar_{ij}} = \frac{1}{Mar_{ij}} \cdot \frac{\partial Mar_{ij}}{\partial\left(\Gamma_t^i/\Gamma_t^j\right)} \cdot \frac{d\left(\Gamma_t^i/\Gamma_t^j\right)}{dt} \quad (2)$$

where *Bias* measures the direction of technological change. A positive value indicates capital-biased technological change, a negative value indicates labor-biased technological change, and a value of zero corresponds to neutral technological change.

However, because fluctuations in factor efficiency may lead to frequent sign changes in the *Bias* index—thereby hindering clear interpretation and failing to capture the intensity of technological bias—this study adopts the cumulative value of the bias index to characterize both the direction and magnitude of technological change. Following existing literature [21], 1979 is used as the base year, and the ratio of marginal products is normalized to unity. The cumulative measure of technological direction is then defined as

$$B_t^{ij} = 1 \times \left(1 + Bias_{1979}^{ij}\right) \times \cdots \times \left(1 + Bias_{t-1}^{ij}\right)\left(1 + Bias_t^{ij}\right) \quad (3)$$

To estimate the direction and magnitude of biased technological change across Chinese provinces, this paper further extends the two-factor CES production function proposed by Le'on-Ledesma, McAdam and Willman [24]. Given the essential role of land in agricultural production, we augment the standard framework by incorporating land as a third input, thereby constructing a three-factor CES production function that includes capital, labor, and land:

$$Y_t = F(\Gamma_t^K K_t, \Gamma_t^L L_t, \Gamma_t^C C_t) = [(\Gamma_t^K K_t)^{\frac{\sigma-1}{\sigma}} + (\Gamma_t^L L_t)^{\frac{\sigma-1}{\sigma}} + (\Gamma_t^C C_t)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \quad (4)$$

where t denotes time, while Y, K, L, and C represent output, capital input, labor input, and land input, respectively. The parameter σ denotes the elasticity of substitution; when $\sigma = 1$, the specification collapses to the Cobb–Douglas production function. When these components are equal, i.e., $\Gamma_t^K = \Gamma_t^L = \Gamma_t^C$, technological change is Hicks-neutral, implying no factor bias. When they differ, the framework accommodates various forms of biased technological change, thereby providing a flexible and general specification.

To ensure comparability and eliminate scale inconsistencies, the CES production function is standardized following a common normalization point [24]. The standardized three-factor CES production function can be expressed as[3]

$$Y_t = Y_0\left[\alpha\left(\frac{\Gamma_t^K K_t}{\Gamma_0^K K_0}\right)^{\frac{\sigma-1}{\sigma}} + \beta\left(\frac{\Gamma_t^L L_t}{\Gamma_0^L L_0}\right)^{\frac{\sigma-1}{\sigma}} + \gamma\left(\frac{\Gamma_t^C C_t}{\Gamma_0^C C_0}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

where subscript 0 denotes the benchmark point. The parameters α, β and γ represent the income shares of capital, labor, and land at the benchmark, satisfying $\alpha+\beta+\gamma=1$.

To address the identification problem whereby the elasticity of substitution and the direction of technological bias cannot be simultaneously identified, we assume that factor-augmenting technological change follows an exponential growth process:

$$\Gamma_{t,t_0}^i = \Gamma_0^i e^{g_i(t,t_0)} \tag{6}$$

Taking logarithms and differentiating with respect to time yields the growth rate of factor efficiency:

$$\frac{\dot{\Gamma}_t^i}{\Gamma_t^i} = \frac{\partial\Gamma_t^i/\partial t}{\Gamma_t^i} = \frac{\partial(\Gamma_0^i e^{g_i(t,t_0)})/\partial t}{\Gamma_t^i} = \frac{\partial g_i}{\partial t} = \dot{g}_i(t,t_0),\ \ i=K,L,C \tag{7}$$

The parameter $g_i(t,t_0)$ serves a dual role: it governs both the level and the growth rate of factor-augmenting technological change. Substituting Equations (5)–(7) into Equation (2) yields the index of technological direction:

$$Bias_t = \begin{bmatrix} Bias_t^{KL} \\ Bias_t^{KC} \\ Bias_t^{LC} \end{bmatrix} = \left(\frac{\sigma-1}{\sigma}\right)\begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \\ 0 & 1 & -1 \end{bmatrix}\begin{bmatrix} \frac{\dot{\Gamma}_t^K}{\Gamma_t^K} & \frac{\dot{\Gamma}_t^L}{\Gamma_t^L} & \frac{\dot{\Gamma}_t^C}{\Gamma_t^C} \end{bmatrix}' \tag{8}$$

Finally, this index is accumulated according to Equation (3) to obtain a measure that captures both the direction and magnitude of biased technological change.

3.1.2. Parameter Estimation

We estimate the model using a normalized supply-side system, which integrates the standardized CES production function with the first-order conditions of profit maximization. This framework yields a system of four equations, consisting of three factor demand equations (for capital, labor, and land) and the production function itself.

The growth rate of factor-augmenting technological change is specified using a Box–Cox functional form:

$$g_i(t,t_0) = \varepsilon_i t_0 \lambda_i^{-1}[(\frac{t}{t_0})^{\lambda_i} - 1],\ \ i=K,L,C \tag{9}$$

where the parameter ε_i governs the direction and magnitude of factor-augmenting technological change, and λ_i captures the curvature of the technology, thereby determining the dynamic evolution of the growth rate.

Following standard practice, the normalization point is defined using sample averages. Specifically, the normalization incorporates a scale parameter ξ and sets the benchmark values of capital, labor, and land based on their sample geometric means, while output is normalized using its arithmetic mean.

We assume an imperfectly competitive market structure characterized by a constant markup. Based on the first-order conditions, the normalized supply-side system under imperfect competition can be written as[4]

$$\left\{\begin{array}{l}\ln r_t = \ln\left(\frac{\alpha}{1+\mu}\frac{\xi\overline{Y}}{\overline{K}}\right) + \frac{1}{\sigma}\ln\left(\frac{Y_t/\xi\overline{Y}}{K_t/\overline{K}}\right) + \frac{\sigma-1}{\sigma}\varepsilon_K\bar{t}\lambda_K^{-1}\left[\left(\frac{t}{\bar{t}}\right)^{\lambda_K}-1\right] \\ \ln w_t = \ln\left(\frac{\beta}{1+\mu}\frac{\xi\overline{Y}}{\overline{L}}\right) + \frac{1}{\sigma}\ln\left(\frac{Y_t/\xi\overline{Y}}{L_t/\overline{L}}\right) + \frac{\sigma-1}{\sigma}\varepsilon_L\bar{t}\lambda_L^{-1}\left[\left(\frac{t}{\bar{t}}\right)^{\lambda_L}-1\right] \\ \ln e_t = \ln\left(\frac{\gamma}{1+\mu}\frac{\xi\overline{Y}}{\overline{C}}\right) + \frac{1}{\sigma}\ln\left(\frac{Y_t/\xi\overline{Y}}{C_t/\overline{C}}\right) + \frac{\sigma-1}{\sigma}\varepsilon_C\bar{t}\lambda_C^{-1}\left[\left(\frac{t}{\bar{t}}\right)^{\lambda_C}-1\right] \\ \ln\frac{Y_t}{\xi\overline{Y}} = \frac{\sigma}{\sigma-1}\ln\left[\begin{array}{l}\alpha\left(\frac{K_t}{\overline{K}}e^{\varepsilon_K\bar{t}\lambda_K^{-1}((t/\bar{t})^{\lambda_K}-1)}\right)^{\frac{\sigma-1}{\sigma}} + \beta\left(\frac{L_t}{\overline{L}}e^{\varepsilon_L\bar{t}\lambda_L^{-1}((t/\bar{t})^{\lambda_L}-1)}\right)^{\frac{\sigma-1}{\sigma}} \\ +\Gamma\left(\frac{C_t}{\overline{C}}e^{\varepsilon_C\bar{t}\lambda_C^{-1}((t/\bar{t})^{\lambda_C}-1)}\right)^{\frac{\sigma-1}{\sigma}}\end{array}\right]\end{array}\right. \tag{10}$$

Given that the three-factor CES framework results in a system of four nonlinear equations, we employ the nonlinear seemingly unrelated regression (NLSUR) method for estimation. This approach effectively accounts for potential cross-equation error correlations and improves estimation efficiency. The initialization of parameters and the identification of the global optimum follow the procedures outlined in León-Ledesma et al. [40]. For the key parameter—the elasticity of substitution σ—we implement a grid search over multiple initial values and select the preferred estimate based on the log-determinant (Log-Det) criterion and global optimization performance.

3.2. Dagum Gini Coefficient and Decomposition

To quantify regional disparities in the direction of agricultural technological change and identify their sources, this paper adopts the Dagum Gini decomposition framework. This approach explicitly accounts for the spatial distribution of observations and effectively addresses issues related to cross-group overlap and the decomposition of inequality sources.

The overall Gini coefficient G is computed as

$$G = \sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|/2n^2\mu \quad \mu_h \le \cdots \mu_j \cdots \le \cdots \le \mu_k \tag{11}$$

where k denotes the number of regions and n the total number of provinces. Let n_j and n_h represent the number of provinces in regions j and h, respectively. Denote by y_{ji} the level of agricultural biased technological progress in province i within region j. The overall mean is given by μ, while μ_j denotes the regional mean for region j. Regions are ordered according to their mean levels of biased technological progress.

The within-region Gini coefficient G_{jj} and the between-region Gini coefficient G_{jh} are given by

$$\begin{array}{l} G_{jj} = \dfrac{\frac{1}{2\mu_j}\sum\limits_{i=1}^{n_j}\sum\limits_{r=1}^{n_j}\left|y_{ji}-y_{jr}\right|}{n_j^2} \\ G_{jh} = \sum\limits_{i=1}^{n_j}\sum\limits_{r=1}^{n_h}\dfrac{\left|y_{ji}-y_{hr}\right|}{n_j n_h(\mu_j+\mu_h)} \end{array} \tag{12}$$

Following Dagum's decomposition, the overall Gini coefficient can be decomposed into three components: the within-region inequality component (G_w), the net between-region inequality component (G_{nb}), and the transvariation (overlap) component (G_t), such that: G = G_w + G_{nb} + G_t. These components are defined as

$$
\begin{aligned}
G_w &= \sum_{j=1}^{k} G_{jj} p_j s_j \\
G_{nb} &= \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} \left(p_j s_h + p_h s_j\right) D_{jh} \\
G_t &= \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} \left(p_j s_h + p_h s_j\right) \left(1 - D_{jh}\right)
\end{aligned} \tag{13}
$$

where $p_j = \frac{n_j}{n}$, $s_j = \frac{n_j \mu_j}{n\mu}$, d_{jh} denotes the expected difference in agricultural biased technological progress between regions j and h. The term D_{jh} captures the degree of distributional overlap (transvariation) between the two regions, defined as the expected value of pairwise comparisons across regions. The functions F_j and F_h denote the cumulative distribution functions of regions j and h, respectively, and reflect the extent of interaction and overlap between regional distributions.

3.3. Kernel Density Estimation

Kernel density estimation (KDE) provides a nonparametric approach to estimating the distribution of a random variable using a continuous density function. It captures key distributional features, including location, shape, and dispersion, and is widely applied in the analysis of spatial distribution dynamics and regional inequality. In this study, KDE is employed to explore the temporal evolution of biased technological change under land constraints, revealing whether regional differences in factor-related productivity tend to widen, narrow, or exhibit polarization over time. In this study, it is employed to reveal how regional differences in biased technological change under land constraints evolve and to identify the main sources driving disparities in factor-related productivity across regions.

Formally, the kernel density estimator for a random variable X is defined as

$$
f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{14}
$$

where N denotes the number of observations, X_i represents independently and identically distributed (i.i.d.) samples, h is the bandwidth parameter, and $K(\cdot)$ is the kernel function. The kernel function serves as a smoothing function that assigns weights to observations. In this study, the Gaussian kernel is employed due to its desirable smoothness properties. The choice of bandwidth h is critical, as it governs the trade-off between bias and variance in the estimation: smaller bandwidths capture more local variation but may introduce noise, whereas larger bandwidths produce smoother estimates at the cost of potential oversmoothing.

The Gaussian kernel function is specified as

$$
K(\mathrm{x}) = \left(1/\sqrt{2\pi}\right) \exp\left(-x^2/2\right) \tag{15}
$$

3.4. Dynamic Spatial Convergence Models

Two standard approaches to convergence analysis are σ-convergence and β-convergence. σ-convergence refers to a decline in the dispersion of a variable across regions over time. In this study, σ-convergence is measured using the coefficient of variation as a standard indicator of dispersion. It is employed to assess whether regional disparities in biased technological change tend to narrow over time, thereby indicating convergence in factor-related productivity under land constraints.

$$\sigma = \frac{\sqrt{\sum_{i-1}^{n_j}\left(B_{ij} - \overline{B_{ij}}\right)^2 / n_j}}{\overline{B_{ij}}} \tag{16}$$

where B_{ij} denotes the level of agricultural biased technological progress in province i within region j, and n_j represents the number of provinces in region j.

From the perspective of regional coordination, the spatial interactions of agricultural technological change in China extend beyond simple geographic dependence. In addition to spatial agglomeration and dependence, they may also involve spatial competition and spillover effects. To account for these features, this paper employs dynamic spatial panel models to test for β-convergence.

We begin with an absolute β-convergence specification based on the Spatial Durbin Model (SDM), which provides a general framework encompassing both spatial lag and spatial error structures:

$$\ln\left(\frac{B_{i,t+1}}{B_{i,t}}\right) = \alpha + \beta\ln(B_{i,t}) + \rho\sum_{j=1}^{n} W_{ij}\ln\left(\frac{B_{j,t+1}}{B_{j,t}}\right) + \theta\sum_{j=1}^{n} W_{ij}\ln(B_{j,t}) + \mu_i + v_t + \varepsilon_{it} \tag{17}$$

To further account for heterogeneity in regional resource endowments and economic characteristics, three dynamic spatial panel specifications are considered to examine conditional β-convergence:

$$\ln\left(\frac{B_{i,t}}{B_{i,t-1}}\right) = \beta\ln B_{i,t-1} + \rho\sum_{j=1}^{n} W_{ij}\ln\left(\frac{B_{i,t}}{B_{i,t-1}}\right) + \gamma\ln X_{it} + u_i + v_t + \varepsilon_{it} \tag{18}$$

$$\ln\left(\frac{B_{i,t}}{B_{i,t-1}}\right) = \beta\ln B_{i,t-1} + \gamma\ln X_{it} + u_i + v_t + \varepsilon_{it}\ \varepsilon_{it} = \lambda\sum_{j=1}^{n} W_{it}\varepsilon_{it} + \mu_{it} \tag{19}$$

$$\begin{aligned}\ln\left(\frac{B_{i,t}}{B_{i,t-1}}\right) &= \beta\ln B_{i,t-1} + \gamma\ln X_{it} + \rho\sum_{j=1}^{n} W_{ij}\ln\left(\frac{B_{i,t}}{B_{i,t-1}}\right) \\ &+\varphi\sum_{j=1}^{n} W_{ij}\ln B_{i,t-1} + \eta\sum_{j=1}^{n} W_{ij}\ln X_{it} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{20}$$

In these models, ρ denotes the spatial lag coefficient, capturing spatial dependence in the dependent variable, while λ represents the spatial error coefficient. μ_i and τ_t denote region-specific and time-specific fixed effects, respectively, and ε_{it} is the idiosyncratic error term.

The vector X includes a set of standard control variables, namely regional economic development level, industrial structure, agricultural infrastructure, fiscal support for agriculture, and the urbanization rate.

The spatial weight matrix W_{ij} defines the structure of spatial interactions. While conventional approaches rely on either geographic or economic distance, each has limitations when used in isolation. Therefore, following Zhou et al. [41], this study constructs a geo-economic spatial weight matrix. Specifically, each weight is defined as the product of the reciprocal of the highway distance between provincial capitals and the relative economic size, measured as the ratio of per capita GDP in region i to the national average. This specification captures both geographic proximity and economic similarity in spatial interactions.

3.5. Data Sources and Variable Construction

The data used in this study are drawn from several authoritative sources, including the China Statistical Yearbook, Historical Data of China's GDP Accounting, publications of the National Bureau of Statistics, and the Compilation of National Agricultural Product Cost and Benefit Data. At the provincial level, Tibet is excluded due to substantial missing data. In addition, Hainan and Chongqing are combined with Guangdong and Sichuan, respectively, yielding a balanced panel of 28 provinces. Subject to data availability, the sample period spans from 1978 to 2021. Missing observations are supplemented using interpolation methods.

The construction of variables is detailed below.

Agricultural output: Agricultural output is measured using the income approach, defined as gross agricultural output net of production taxes. Missing observations are supplemented using proportional adjustments based on regional input-output tables. The series is deflated using the value-added index of the primary industry to obtain real values. Factor inputs: Capital input is proxied by agricultural capital stock, which is not directly reported in official statistics and is therefore estimated using the perpetual inventory method (PIM). The depreciation rate and related parameters follow Li [42], and the series is deflated using the price index of agricultural production inputs. Labor input is measured by the number of employed persons in the primary industry. Land input is proxied by total sown area, which captures land use intensity by accounting for multiple cropping. Factor prices: The price of capital is measured as the ratio of agricultural capital depreciation to capital stock. Land rent is estimated using the average output value per unit of cultivated land for major crops, following established approaches in the literature [43]. For missing years, values are imputed based on the estimated relationship between output per unit area and sown area. Labor income is calculated as the residual of agricultural output after deducting capital and land income. Dividing labor income by labor input yields the agricultural wage rate [44]. Control variables: The empirical analysis includes a set of standard controls. Regional economic development is measured by real GDP per capita. Industrial structure is proxied by the share of the primary sector in GDP. Agricultural infrastructure is captured by the ratio of effectively irrigated area to total sown area. Fiscal support for agriculture is measured as the share of government agricultural expenditure in primary sector GDP. Finally, the urbanization rate is defined as the proportion of urban residents in the total population.

Table 1 summarizes variable definitions, measurements, data sources, and processing procedures. Data management, variable construction, and empirical analyses were conducted using Stata 18.0. Specifically, the normalized CES supply-side system was estimated using nonlinear seemingly unrelated regression (NLSUR) in Stata 18.0; Dagum Gini decomposition and kernel density estimation were implemented through customized procedures in MATLAB; and spatial econometric analyses, including spatial convergence models, were estimated using the xsmle package in Stata 18. Figures and statistical outputs were generated using Stata.

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Table 1. Variables, definitions, data sources, and processing methods.

Category	Variable	Measurement	Data Source
Agricultural output	Agricultural output value	Agricultural GDP excluding net production taxes	China Statistical Yearbook; Historical GDP Accounting Data of China
Capital input	Agricultural capital stock	Estimated using perpetual inventory method	China Statistical Yearbook
Labor input	Agricultural labor	Employment in primary industry	National Bureau of Statistics
Land input	Agricultural land	Crop sown area	Compilation of National Agricultural Product Cost and Benefit Data
Capital price	Capital cost	Depreciation/capital stock	Calculated
Labor price	Labor cost	Labor income/labor input	Calculated
Land price	Land rent	Estimated from crop output per unit cultivated land	Calculated
Economic development	GDP per capita	Real GDP per capita	China Statistical Yearbook
Industrial structure	Industrial structure	Share of primary industry in GDP	China Statistical Yearbook
Agricultural infrastructure	Irrigation level	Effective irrigation area/total sown area	China Statistical Yearbook
Fiscal support	Fiscal support to agriculture	Agricultural expenditure/primary industry GDP	China Statistical Yearbook
Urbanization	Urbanization rate	Urban population/total population	National Bureau of Statistics

To provide a clearer overview of the empirical design and analytical procedures, Figure 2 illustrates the integrated framework of this study, including data integration, measurement of biased technological change, regional disparity decomposition, distributional dynamics, and spatial convergence analysis under land constraints.

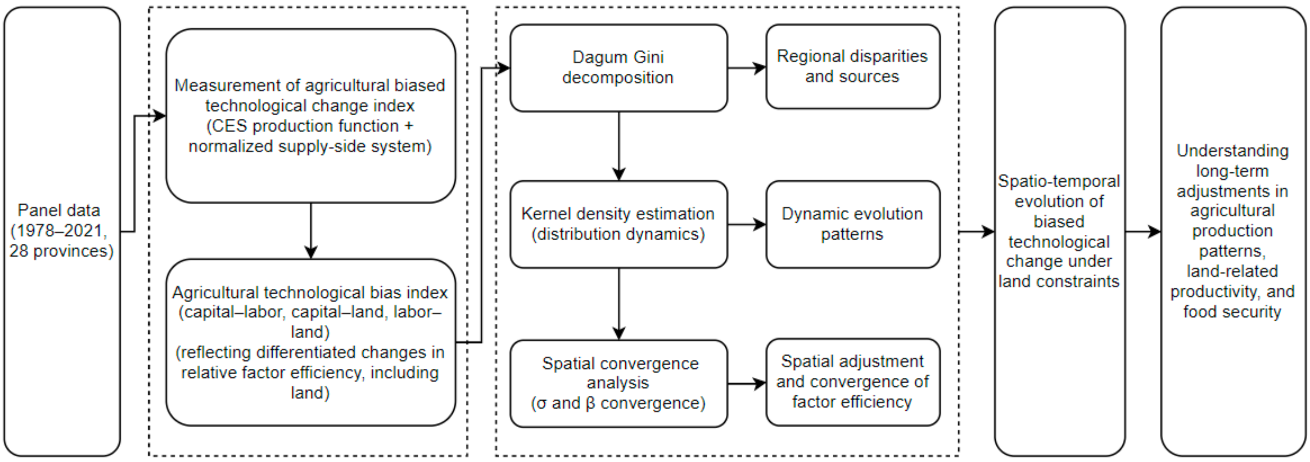


Figure 2. Empirical framework for analyzing biased technological change under land constraints.

4. Measurement Results and Regional Evolution of the Direction of Technological Progress

4.1. Measurement Results

Figure 3 presents the evolution of agricultural technological progress bias in China during the sample period. At the national level, technological progress is predominantly labor-biased, indicating that technological change has contributed more to improving labor productivity than other production factors. Specifically, the average capital–labor bias index is 0.61 and exhibits a declining trend over time, suggesting an increasingly stronger orientation toward labor-augmenting technological progress.

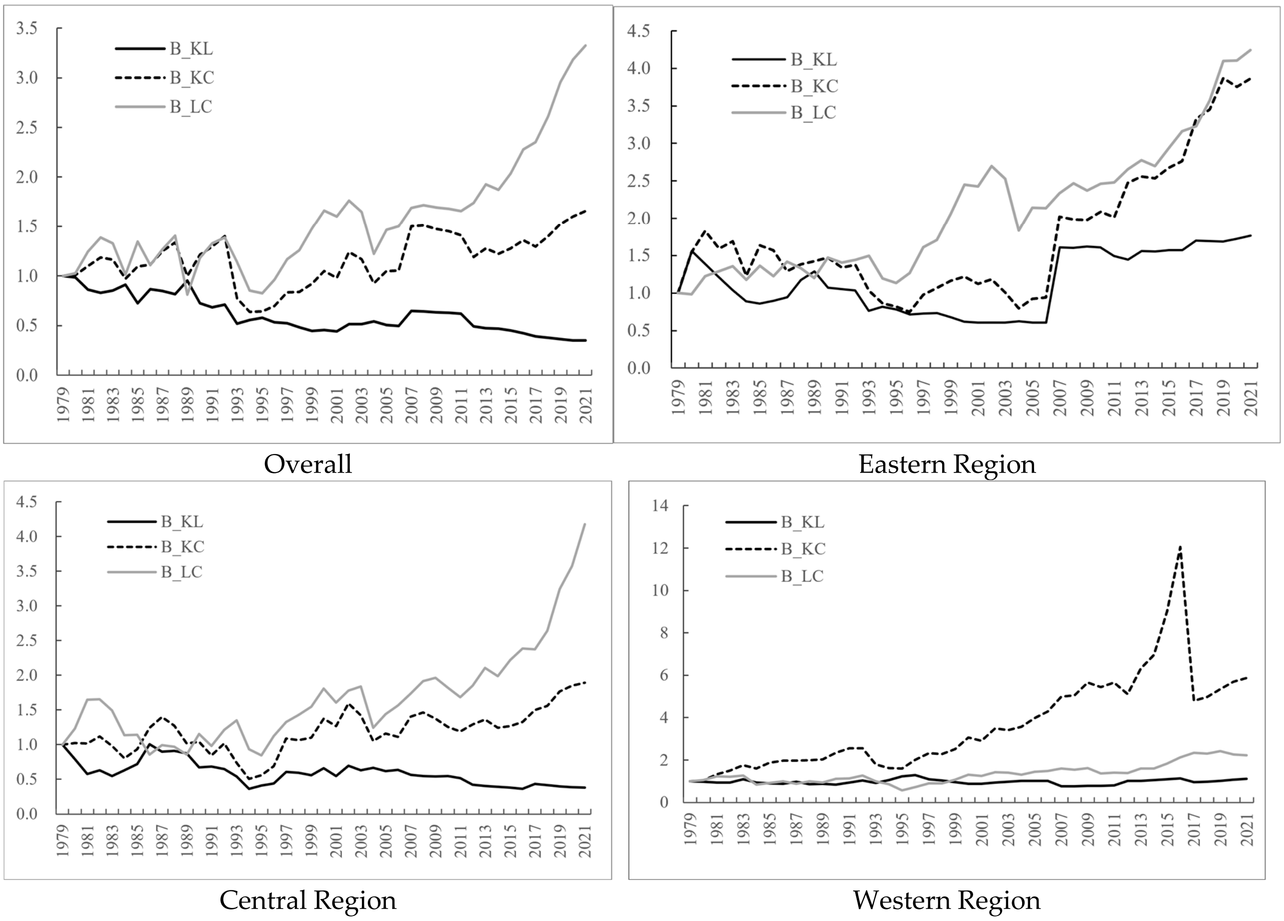


Figure 3. Index of agricultural technological progress direction in China.

In contrast, the average indices of capital–land and labor–land technological bias are 1.16 and 1.58, respectively, indicating that technological progress increasingly favors capital and labor relative to land. Both indices display a mild decline followed by a pronounced increase, with a turning point around 1995. This pattern suggests that technological progress in early periods was more closely associated with improving land productivity, whereas subsequent development gradually shifted toward capital- and labor-augmenting pathways. Such changes imply that agricultural growth has increasingly relied on improving non-land factor efficiency to sustain output growth under tightening farmland constraints, reflecting a transition from land-dependent expansion to technology-driven intensification.

This transition may be closely related to institutional change and structural transformation in Chinese agriculture. During the early reform period, the Household Responsibility System substantially improved production incentives and land allocation efficiency, thereby enhancing land-related productivity. Similar findings have been reported in studies emphasizing the role of institutional reform in improving agricultural efficiency and resource allocation [42]. However, since the mid-1990s, rapid industrialization and urbanization have accelerated rural labor migration and altered relative factor scarcity. Under increasing labor shortages and stricter land constraints, agricultural production gradually shifted toward capital substitution and labor-saving technologies, consistent with the induced innovation theory suggesting that changes in factor scarcity reshape technology direction choices [12,17]. Meanwhile, the implementation of policies promoting agricultural modernization, such as the "948 Program", further encouraged capital accumulation and technological upgrading in agriculture.

Another possible explanation relates to farmland protection and resource constraints. The strengthening of cultivated land protection policies and limited opportunities for farmland expansion may have reduced the contribution of extensive land use to agricultural growth. Consequently, improvements in agricultural productivity increasingly depended on enhancing factor efficiency rather than increasing land inputs. This interpretation supports the argument that technological progress under land scarcity tends to favor pathways capable of compensating for constrained land resources through capital deepening and productivity enhancement.

At the regional level, substantial heterogeneity is observed. In eastern China, all three bias indices exceed one, indicating a clear capital-oriented pattern of technological progress. This finding is broadly consistent with previous studies showing that economically developed regions are more likely to attract advanced production factors and adopt capital-intensive technologies [21]. Compared with central and western regions, the eastern region possesses stronger infrastructure conditions, higher agricultural mechanization levels, and greater innovation capacity, enabling more effective substitution of scarce land resources with capital inputs. As a result, higher land-related productivity may be achieved through technology direction choices favoring capital accumulation. This finding further supports Hypothesis 2, which proposes that heterogeneous land constraints and factor endowments induce differentiated regional pathways of technological progress.

4.2. Regional Disparities in the Direction of Agricultural Technological Progress and Their Decomposition

As illustrated in Figure 4, the Gini coefficients of the three types of factor-biased technological progress indices exhibit a persistent upward trend over the sample period, indicating increasing regional divergence in the direction of agricultural technological change. From a land-use perspective, this growing divergence suggests that regions have adopted increasingly differentiated technological pathways to respond to heterogeneous land constraints, potentially generating unequal improvements in land-related productivity and agricultural performance.

Dynamic decomposition reveals that the sources of these disparities vary substantially across different dimensions of technological bias. For the capital–labor bias index, interregional differences gradually replace transvariation density as the dominant source after 2007. This shift implies that disparities in economic development, agricultural modernization, and factor endowments have become increasingly important in shaping regional technology direction choices. A possible explanation is the acceleration of regional imbalance during China's rapid industrialization and urbanization period, which widened differences in capital accumulation, labor migration, and agricultural investment among eastern, central, and western regions. Similar findings have been reported in studies showing that regional heterogeneity in technological innovation tends to increase alongside uneven economic development [8,21]. Meanwhile, steadily rising intraregional disparities suggest that technological adoption has become increasingly uneven even within the same region, possibly reflecting differences in local infrastructure, mechanization levels, and access to agricultural innovation.

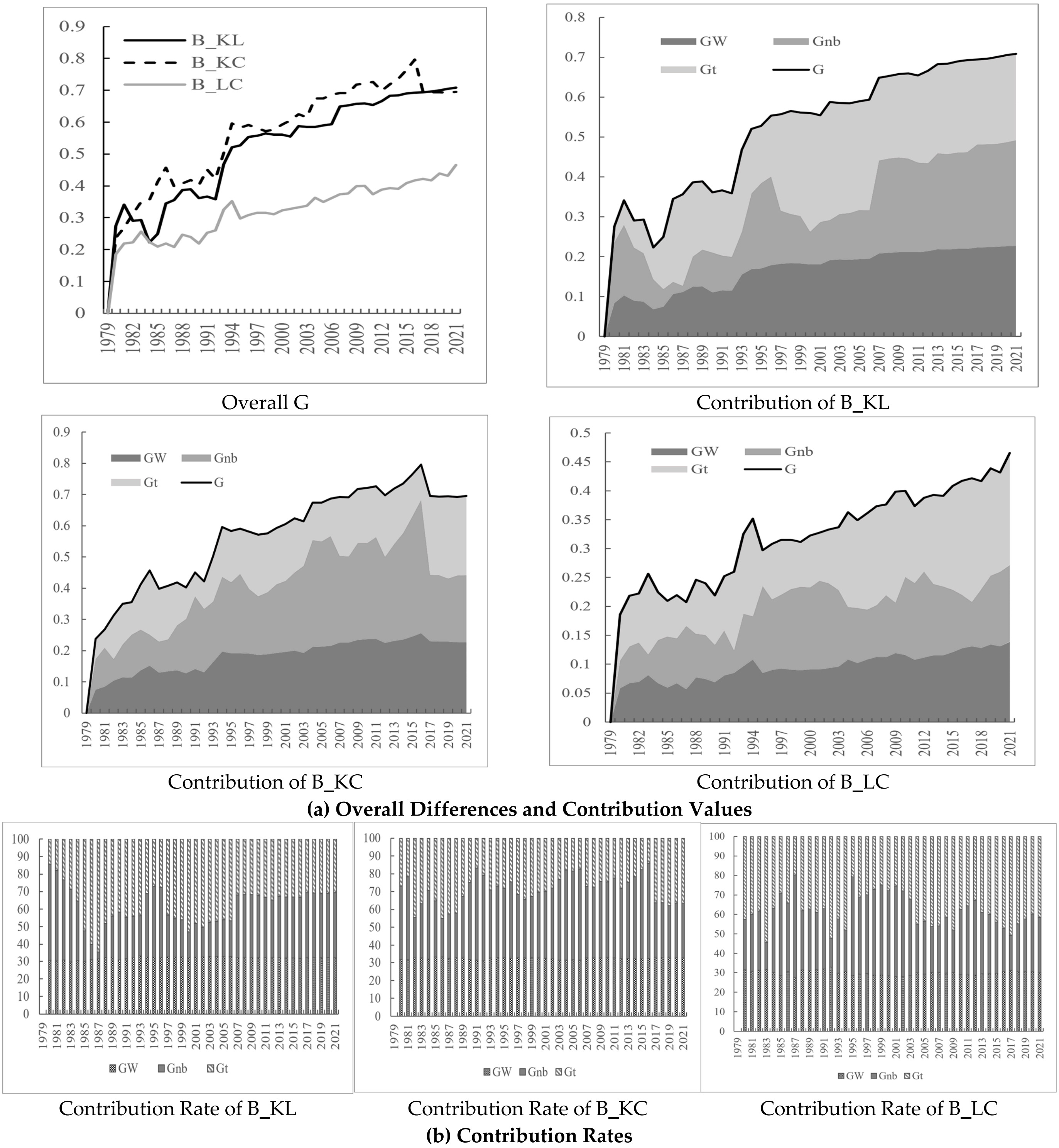


Figure 4. Overall differences and sources of China's agricultural technical progress bias index.

For the capital–land bias index, disparities evolve from expansion to relative stabilization, with interregional differences remaining the dominant contributor throughout most periods. This pattern highlights that the interaction between capital accumulation and land constraints constitutes a major source of regional heterogeneity. Regions with stronger capital investment capacity may improve agricultural output through mechanization and technology substitution, whereas land-constrained but capital-deficient regions may experience slower improvements in land-related productivity. Such findings are broadly consistent with previous evidence that differences in resource endowments and factor allocation significantly influence agricultural development trajectories [17,44]. Another possible explanation lies in differences in regional farmland protection intensity and infrastructure conditions, which may alter the capacity of agricultural systems to substitute land inputs through technological upgrading.

In contrast, transvariation density remains the dominant contributor to labor–land bias disparities, suggesting substantial overlap and complex interactions across regions in the adjustment of labor and land inputs. This may reflect the widespread effects of rural labor migration and demographic transition, which have reshaped agricultural labor availability nationwide. Unlike capital accumulation, labor outflow affects most regions simultaneously but to varying degrees, generating overlapping yet differentiated patterns of labor–land substitution.

Taken together, regional disparities are greatest for capital–land bias, followed by capital–labor and labor–land bias. This finding suggests that capital–land interactions constitute the most important source of heterogeneous agricultural adaptation under land constraints. In other words, differences in capital accessibility and land resource conditions largely determine how effectively regions improve land-related productivity without expanding cultivated land. This result supports Hypothesis 1 and Hypothesis 2, indicating that land scarcity and heterogeneous factor endowments induce differentiated technology direction choices across regions. Although disparities associated with capital-related biases exhibit partial convergence over time, labor–land disparities continue to widen, implying increasing divergence in regional capacities to adjust labor allocation and sustain agricultural production under constrained land resources.

4.3. Intraregional Disparities in the Direction of Agricultural Technological Progress

Figure 5 depicts the evolution of intraregional disparities in technological bias across eastern, central, and western China. For the capital–labor bias index, both the eastern and central regions exhibit sustained increases in intraregional disparities, with the eastern region showing the fastest growth. This finding suggests that even within economically developed regions, provinces differ substantially in their ability to adopt capital-intensive technologies or improve labor productivity, resulting in uneven technological pathways.

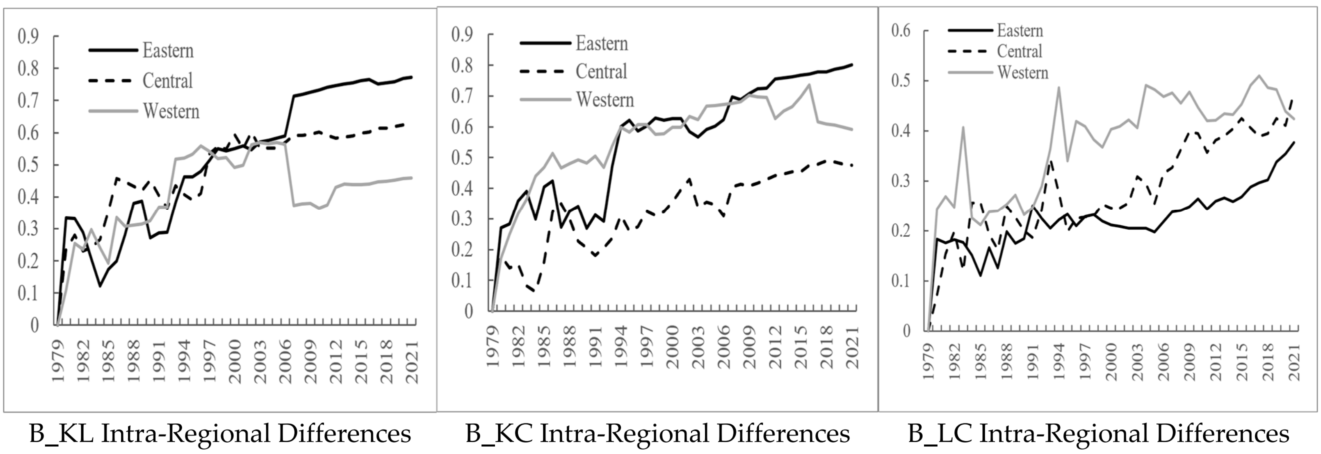


Figure 5. Intra-regional differences in China's agricultural technical progress direction (Gini Coefficient).

The rapid expansion of intraregional disparities in the eastern region may be attributed to uneven processes of agricultural modernization. Although eastern provinces generally possess stronger economic foundations and innovation capacity, differences in industrialization levels, agricultural mechanization, urbanization, and factor mobility remain substantial. Consequently, some provinces have achieved faster transitions toward capital-intensive and technology-driven agriculture, whereas others continue to rely more heavily on traditional production patterns. Similar evidence has been reported in studies on regional technological innovation, which find that advanced regions often exhibit stronger internal divergence because leading areas benefit disproportionately from technological accumulation and resource concentration [21].

In contrast, the western region displays a fluctuating trajectory characterized by expansion followed by contraction, indicating greater instability in technological evolution. One possible explanation is that western China has experienced alternating influences from policy support and resource constraints. National development strategies, including the Western Development Program and infrastructure investment, may have partially reduced technological disparities by improving factor mobility and agricultural conditions. However, persistent limitations in capital accumulation, human resources, and agricultural infrastructure continue to constrain the diffusion of advanced technologies. Similar fluctuation patterns are also observed for capital–land and labor–land bias indices, suggesting that technological responses to land constraints remain relatively unstable in less-developed regions.

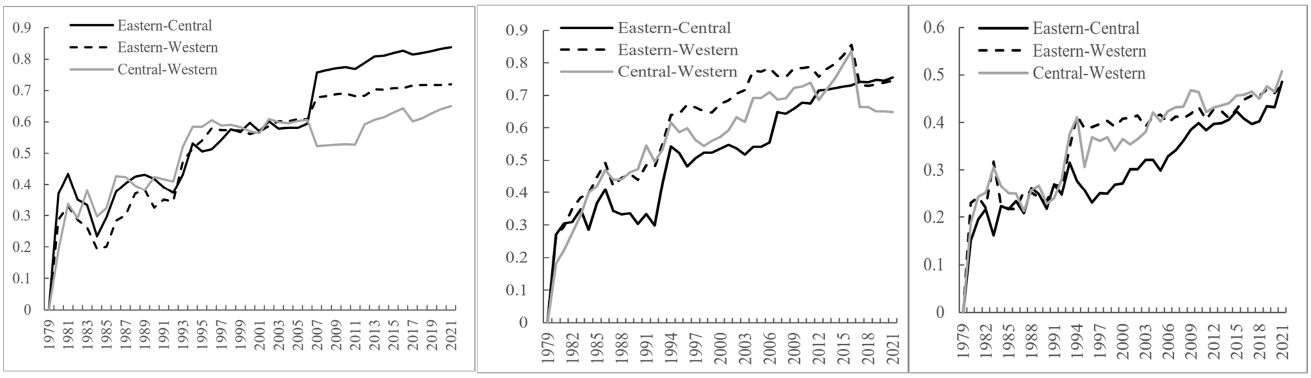
From a spatial perspective, intraregional disparities in capital–labor bias decline progressively from east to west, whereas labor–land disparities exhibit the opposite pattern. These contrasting gradients imply that different regions rely on distinct pathways to adjust agricultural production under heterogeneous resource constraints. In more developed regions, technological choices are more closely associated with capital accumulation and mechanization, while in less-developed regions, labor allocation and land utilization remain more important determinants of technological evolution [45].

From the perspective of land use efficiency, increasing intraregional disparities indicate that provinces within the same region have adopted increasingly differentiated strategies to respond to farmland constraints. In eastern China, widening disparities may reflect heterogeneous pathways toward intensive land use and agricultural modernization. By contrast, in western regions, fluctuating disparities may indicate uneven capacities to improve land-related productivity due to differences in infrastructure conditions, fiscal support, and access to technological innovation. This finding supports Hypothesis 2, suggesting that heterogeneous factor endowments and land constraints contribute to differentiated regional patterns of technological bias.

4.4. Interregional Disparities in the Direction of Agricultural Technological Progress

Figure 6 presents the evolution of interregional disparities in agricultural technological bias. For the capital–labor bias index, disparities between eastern and central China, as well as between eastern and western China, continue to widen, with the east-central gap becoming more pronounced after 2008. This pattern suggests increasing divergence in technology direction choices, likely associated with uneven economic development, labor mobility, and agricultural modernization across regions. Similar findings have been reported in studies on regional technological heterogeneity in China [23].

For the capital–land and labor–land bias indices, disparities are largest between eastern and western regions, followed by central-western differences. This indicates that differences in land resource conditions and capital availability remain important determinants of regional technological pathways. Compared with western regions, eastern provinces possess stronger infrastructure, higher mechanization levels, and better access to capital, enabling more effective substitution of constrained land inputs through technological upgrading.



B_KL Inter-Regional Differences B_KC Inter-Regional Differences B_LC Inter-Regional Difference

Figure 6. Inter-regional differences in China's agricultural technical progress bias (Gini Coefficient).

From a land-use perspective, these interregional disparities imply uneven improvements in land-related productivity across regions. Regions with stronger capital accumulation and innovation capacity tend to achieve higher land use efficiency, whereas regions facing multiple resource constraints exhibit slower technological upgrading. This finding is consistent with previous evidence that regional differences in factor endowments contribute to unequal agricultural development trajectories [42,44].

Overall, the results indicate that spatial heterogeneity in factor endowments plays an important role in shaping agricultural technology direction choices. Persistent east–west disparities further suggest that regional differences in responding to land constraints remain substantial, supporting Hypothesis 2 regarding heterogeneous technological pathways under constrained resources.

4.5. Biased Technological Change and Land Use Efficiency

The empirical results indicate that biased technological change is closely associated with differences in land-related productivity under increasing land constraints. Specifically, the rising labor–land and capital–land bias indices suggest that agricultural growth increasingly relies on improving non-land factor productivity rather than expanding cultivated land. This pattern reflects a gradual transition from land-dependent growth toward more intensive production.

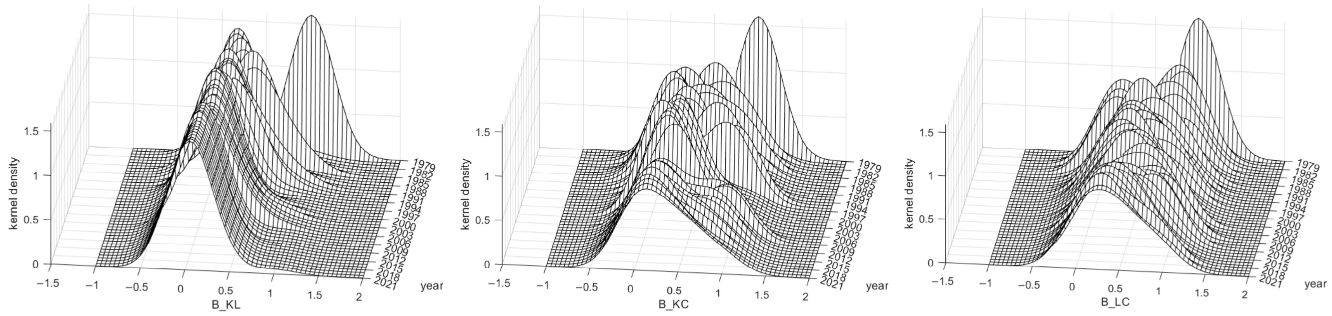
At the same time, regional heterogeneity in technological bias implies uneven improvements in land use efficiency. Regions with stronger capital accumulation and innovation capacity—particularly eastern China—appear better able to improve agricultural output under constrained land resources, whereas less-developed regions face slower gains due to limitations in infrastructure, factor mobility, and technological adoption.

Although convergence results indicate partial catch-up over time, persistent regional disparities suggest that improvements in land-related productivity remain uneven. Overall, biased technological change is not neutral with respect to land use outcomes; instead, it reflects differentiated pathways through which regions adapt agricultural production to farmland constraints and food security pressures.

5. Temporal Dynamics of Agricultural Technological Progress Bias

5.1. National Level

As shown in Figure 7, kernel density estimates reveal differentiated dynamic patterns across the three bias indices, reflecting evolving technology direction choices under changing factor constraints.



B_KL overall B_KC overall B_LC overall

Figure 7. Distribution dynamics of technical progress directions at the national level.

In terms of distributional shifts, the capital–labor index moves slightly leftward, indicating a gradual strengthening of labor-biased technological progress. The labor–land index follows a decline-increase trajectory, suggesting a renewed intensification of labor-related productivity relative to land, whereas the capital–land index remains relatively stable. These patterns imply that agricultural growth increasingly depends on improving non-land factor efficiency under tightening land constraints, which is broadly consistent with studies emphasizing induced technological responses to changing factor scarcity [17].

Regarding dispersion, the peak of the capital–labor distribution rises modestly, while the labor–land index shows a slight widening, indicating increasing differentiation in regional technology direction choices. By contrast, the capital–land index exhibits initial expansion followed by mild convergence, suggesting that disparities in capital–land adjustment have partially narrowed over time. This may reflect gradual diffusion of agricultural mechanization and infrastructure improvement across regions.

All three indices display right-skewed distributions with shortening tails, implying that although provinces with stronger technological bias remain, interprovincial differences have moderately narrowed. Similar convergence tendencies have been observed in studies on regional agricultural innovation and technological development [46]. Moreover, the predominantly unimodal distributions suggest limited polarization, indicating that technological evolution occurs through gradual adjustment rather than abrupt divergence.

Overall, national-level dynamics indicate partial convergence alongside persistent heterogeneity. From a land-use perspective, this suggests that improvements in land-related productivity increasingly rely on differentiated but gradually converging technology pathways rather than expansion of cultivated land.

5.2. Regional Level

As shown in Figure 8, temporal dynamics at the regional level exhibit substantial heterogeneity, reflecting differences in factor endowments, development stages, and agricultural modernization across regions.

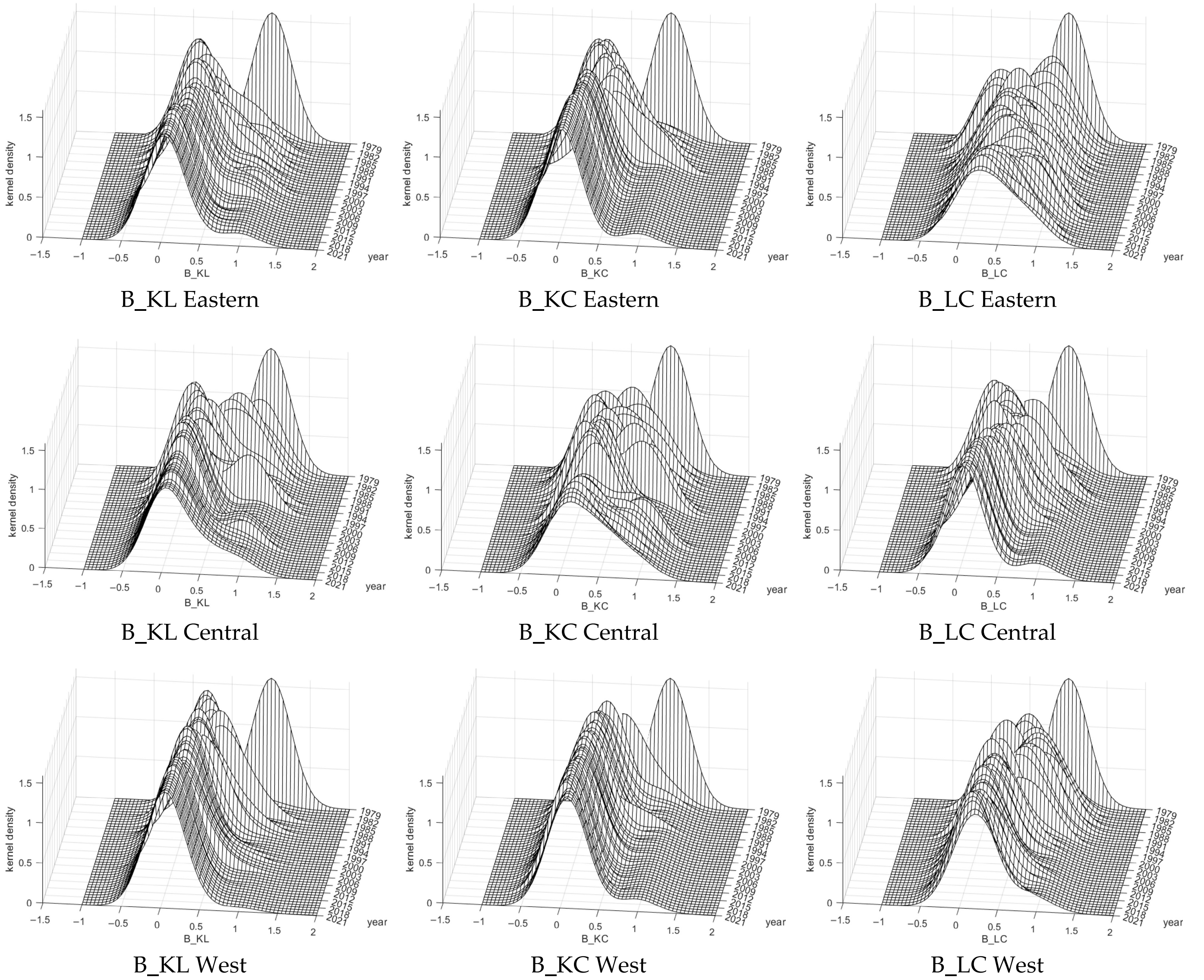


Figure 8. Distribution dynamics of technical progress directions at the regional level.

In the eastern and central regions, most bias indices follow a decline-increase trajectory, with particularly pronounced changes in labor–land bias. This pattern suggests renewed adjustment toward labor-related productivity under increasing land constraints and structural transformation. By contrast, the western region shows relatively stable dynamics, except for the capital–land index, which exhibits an increase-decrease pattern, indicating slower and more constrained technological evolution. Such regional differences are consistent with previous studies emphasizing heterogeneous technological development under uneven economic conditions [21].

Distributional dispersion increases in the eastern and central regions, especially for capital-related biases, implying widening differences in technology adoption and factor substitution within regions. This may reflect unequal capacities to improve agricultural productivity through mechanization and capital accumulation. In contrast, the western region displays a rise followed by a decline in dispersion, suggesting partial convergence in technological pathways, possibly associated with infrastructure improvement and policy support.

Right-skewed distributions remain evident in the eastern and central regions, indicating the persistence of provinces with stronger technological bias. The shortening tails observed in western China imply gradual narrowing of regional differences. Moreover, predominantly unimodal distributions suggest limited technological polarization, indicating gradual adjustment rather than persistent divergence.

Overall, the results show that regions follow distinct technology direction choices under heterogeneous resource constraints. From a land-use perspective, this implies that improvements in land-related productivity remain spatially uneven, despite evidence of partial convergence over time.

6. Convergence of Agricultural Technological Progress Bias in China

6.1. σ-Convergence

Figure 9 shows that, at the national level, the coefficient of variation for the capital–labor and labor–land bias indices exhibits an overall upward trend, while the capital–land index follows an increase-decrease pattern. This indicates that disparities in technological bias have not consistently narrowed over time and that technology direction choices remain differentiated across provinces.

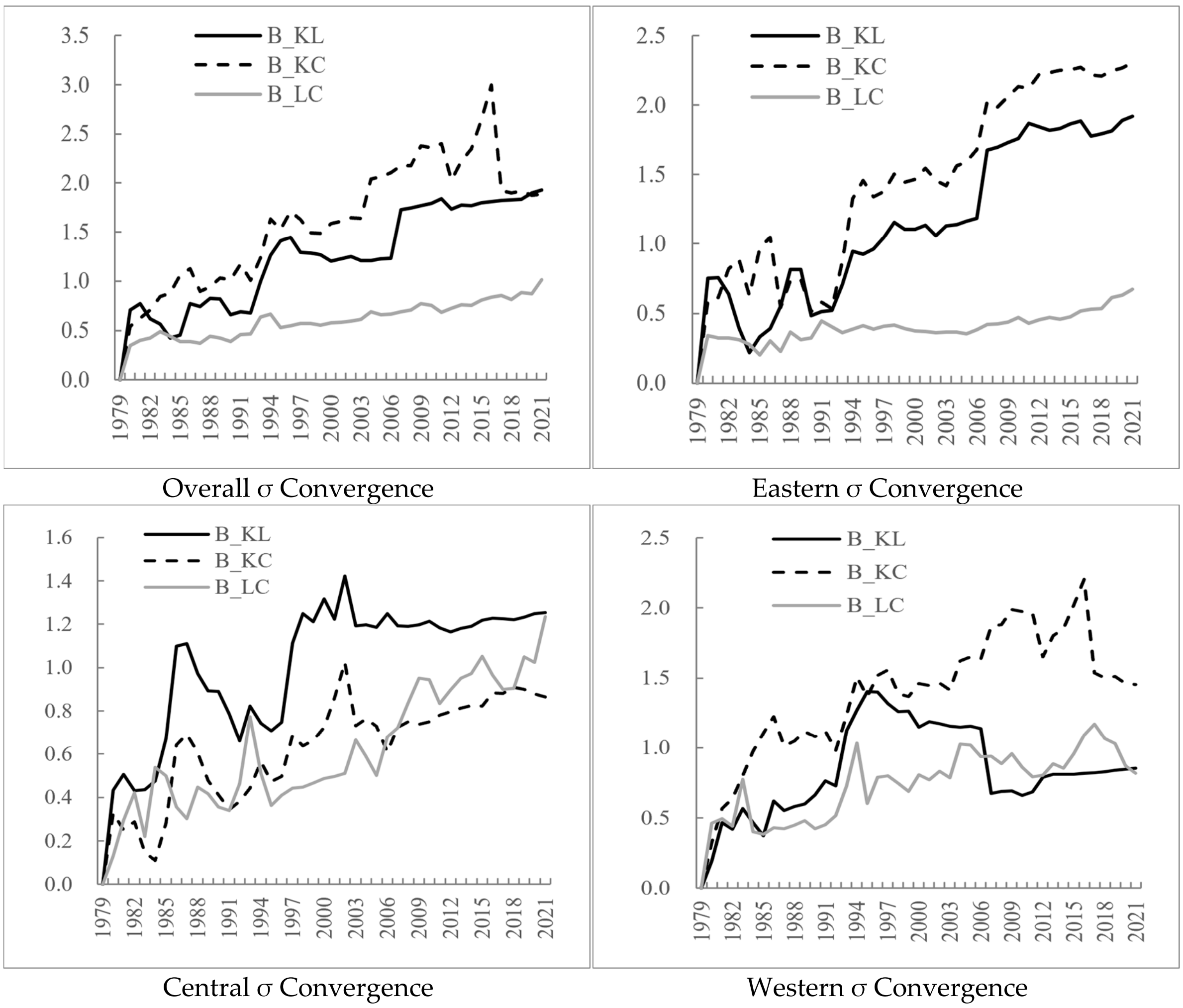


Figure 9. σ-convergence test of agricultural technical progress direction index at national and regional levels.

Similar patterns are observed at the regional level. In eastern China, variation in capital–labor and capital–land bias continues to increase, whereas labor–land bias remains relatively stable but ends above its initial level. In the central region, all three indices display fluctuating yet generally increasing trends. In western China, capital–land bias exhibits the highest variation with an increase-decline pattern, while the remaining indices change more moderately. These differences likely reflect persistent heterogeneity in factor endowments, agricultural modernization, and technology adoption across regions.

Overall, there is no clear evidence of σ-convergence at either the national or regional level. This finding is consistent with the earlier Dagum Gini decomposition results, which show persistent interregional and intraregional disparities. From a land-use perspective, the absence of σ-convergence suggests that improvements in land-related productivity have not occurred uniformly across regions, and structural differences in adapting to land constraints remain substantial.

6.2. β-Convergence

6.2.1. Absolute Β-Convergence

Based on the LM, LR, Wald, and Hausman tests, the estimation results (Table 2) show that all β coefficients are significantly negative, indicating the presence of absolute β-convergence in agricultural technological progress bias.

Table 2. Absolute β-convergence test of agricultural technical progress direction at the national and regional levels.

	Overall			Eastern			Central			Western		
Model	**KL_Sdm**	**KC_Sar**	**LC_Sar**	**KL_Sem**	**KC_Sem**	**LC_Sem**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**
β	−0.093 ***	−0.074 ***	−0.220 ***	−0.031 **	−0.057 ***	−0.184 ***	−0.081 **	−0.149 ***	−0.197 ***	−0.072 **	−0.086 ***	−0.246 ***
	(0.012)	(0.011)	(0.017)	(0.012)	(0.016)	(0.030)	(0.036)	(0.030)	(0.032)	(0.034)	(0.021)	(0.029)
ρ	−0.251 ***	−0.089	0.054				0.019	−0.438 ***	−0.049	0.106	0.372 ***	−0.640 ***
	(0.095)	(0.084)	(0.087)				(0.075)	(0.086)	(0.082)	(0.082)	(0.063)	(0.133)
λ				−0.280 ***	−0.383 ***	−0.089						
				(0.091)	(0.085)	(0.084)						
φ	−0.244 ***						−0.011	−0.118	−0.119	−0.067	0.026	0.139
	(0.067)						(0.043)	(0.082)	(0.076)	(0.053)	(0.041)	(0.138)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
obs	1176	1176	1176	420	420	420	336	336	336	420	420	420

Note: Values in parentheses are standard errors; *** and ** indicate significance at the 1% and 5% levels, respectively.

This finding suggests that provinces with lower initial levels of technological bias tend to catch up over time under similar conditions, consistent with the neoclassical convergence hypothesis. However, convergence speeds vary considerably across regions and bias types. The fastest convergence is observed for labor–land bias in western China, whereas the slowest occurs for capital–labor bias in eastern China. Overall, convergence speeds follow the order: labor–land > capital–land > capital–labor.

The relatively faster convergence in labor–land bias implies that adjustments associated with labor allocation and land utilization may diffuse more quickly across regions than capital-related technological changes. Similar convergence patterns have been reported in studies on regional technological development and agricultural efficiency [46]. By contrast, slower convergence in capital-related bias suggests that differences in capital accumulation and technological capacity remain persistent.

From a land-use perspective, these results indicate gradual convergence in land-related productivity, although heterogeneous convergence speeds imply that regional disparities in adapting to land constraints may continue over the long term.

6.2.2. Conditional Β-Convergence

After controlling for structural factors—including economic development, industrial structure, agricultural infrastructure, fiscal support, and urbanization (Table 3)—the β coefficients remain significantly negative, and convergence speeds increase relative to the absolute case. This indicates that technological bias converges toward region-specific steady states when structural heterogeneity is considered.

Table 3. Conditional β convergence test of technological progress directions.

Model	Overall			Eastern			Central			Western		
	KL_Sdm	**KC_Sdm**	**LC_Sdm**	**KL_Sem**	**KC_Sem**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sar**
β	−0.120 ***	−0.107 ***	−0.244 ***	−0.053 ***	−0.089 ***	−0.295 ***	−0.235 ***	−0.208 ***	−0.244 ***	−0.213 ***	−0.125 ***	−0.307 ***
	(0.013)	(0.013)	(0.017)	(0.016)	(0.019)	(0.034)	(0.039)	(0.036)	(0.036)	(0.034)	(0.025)	(0.030)
ρ	−0.249 ***	−0.146 *	0.102			−0.146	−0.044	−0.478 ***	−0.092	0.032	0.340 ***	−0.629 ***
	(0.095)	(0.087)	(0.087)			(0.093)	(0.077)	(0.087)	(0.084)	(0.086)	(0.066)	(0.129)
λ				−0.288 ***	−0.380 ***							
				(0.091)	(0.085)							
φ	−0.256 ***	−0.203 ***	0.151			−0.182	−0.209 **	−0.215 *	−0.196 **	−0.316 ***	−0.091	
	(0.073)	(0.068)	(0.102)			(0.123)	(0.081)	(0.112)	(0.098)	(0.097)	(0.073)	
PerGDP	0.337 ***	0.394 ***	−0.062	0.211	0.409 *	−0.013	−0.131	0.102	0.111	0.500 ***	0.404 **	0.051
	(0.095)	(0.103)	(0.065)	(0.148)	(0.215)	(0.107)	(0.288)	(0.249)	(0.169)	(0.173)	(0.199)	(0.162)
Industrial structure	−0.081 *	−0.036	0.132 ***	−0.048	−0.046	0.158 ***	−0.211	−0.019	0.206 **	−0.004	−0.009	0.445 ***
	(0.044)	(0.047)	(0.031)	(0.052)	(0.069)	(0.034)	(0.151)	(0.114)	(0.080)	(0.129)	(0.150)	(0.122)
Infras	−0.117 *	0.024	0.094 **	0.016	0.204	0.074	−0.043	0.145	0.009	−0.485 ***	−0.223	0.274 **
	(0.067)	(0.072)	(0.047)	(0.096)	(0.139)	(0.067)	(0.154)	(0.131)	(0.090)	(0.161)	(0.149)	(0.117)
Fiscal	0.052	0.033	−0.080 ***	0.024	0.038	−0.085 **	0.069	−0.006	−0.086 **	0.127 **	0.051	−0.135 ***
	(0.034)	(0.037)	(0.024)	(0.047)	(0.065)	(0.034)	(0.068)	(0.058)	(0.040)	(0.054)	(0.063)	(0.050)
Urban	−0.199 ***	−0.139 **	0.034	−0.126 **	−0.158 *	−0.003	−0.362	−0.278	−0.045	−0.143	0.092	−0.155
	(0.059)	(0.064)	(0.041)	(0.060)	(0.084)	(0.042)	(0.265)	(0.192)	(0.129)	(0.101)	(0.124)	(0.095)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1176	1176	1176	420	420	420	336	336	336	420	420	420

Note: Values in parentheses are standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The overall convergence pattern remains broadly unchanged, with labor–land bias converging the fastest. Regionally, capital-related biases converge most rapidly in the central region, followed by western and eastern China, whereas labor–land bias converges fastest in the western region. This finding suggests that regions with relatively lower initial levels of agricultural modernization may exhibit stronger catch-up effects in adjusting technology direction choices, which is consistent with convergence theory.

Control variables show differentiated effects across regions. Economic development promotes capital-related bias in some areas, while industrial structure generally enhances labor–land bias. Agricultural infrastructure displays region-specific impacts, and fiscal support tends to reduce labor–land bias while encouraging capital deepening in certain regions. Urbanization negatively affects capital-related bias in eastern China. These results imply that differences in development conditions and resource allocation continue to shape regional technological pathways [47].

Overall, conditional convergence results highlight that structural factors influence not only the speed of convergence but also the long-term equilibrium of technology direction choices. From a land-use perspective, improvements in land-related productivity appear to depend increasingly on regional development conditions rather than purely on technological diffusion, emphasizing the importance of heterogeneous adaptation under land constraints.

6.3. Robustness Checks

Due to the long sample period and limited availability of historical provincial data, some variables (e.g., land rent) are measured using proxy estimates. Sensitivity analyses based on alternative factor price definitions are difficult to implement because comparable long-term data are unavailable. Therefore, to further examine model reliability, the baseline geo-economic composite weight matrix is replaced with geographic and economic distance matrices for robustness checks.

The results (Tables 4–7) show that the signs and significance levels of the β coefficients remain broadly consistent with the benchmark estimates. Both absolute and conditional β-convergence persist under alternative spatial weight matrices, indicating that the main conclusions regarding the spatial convergence of agricultural technological bias under land constraints are robust.

Table 4. Absolute β-convergence results under the geographic distance weight matrix.

	Overall			Eastern			Central			Western		
Model	**KL_Sdm**	**KC_Sar**	**LC_Sar**	**KL_Sem**	**KC_Sem**	**LC_Sem**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**
β	−0.091 ***	−0.074 ***	−0.220 ***	−0.031 **	−0.056 ***	−0.187 ***	−0.083 **	−0.161 ***	−0.198 ***	−0.072 **	−0.087 ***	−0.247 ***
	(0.012)	(0.011)	(0.017)	(0.012)	(0.016)	(0.030)	(0.036)	(0.032)	(0.032)	(0.034)	(0.021)	(0.030)
ρ	−0.438 ***	−0.222 **	−0.049				0.029	−0.609 ***	−0.095	0.100	0.386 ***	−0.702 ***
	(0.117)	(0.108)	(0.103)				(0.082)	(0.100)	(0.096)	(0.082)	(0.065)	(0.138)
λ				−0.420 ***	−0.587 ***	−0.142						
				(0.107)	(0.104)	(0.096)						
φ	−0.291 ***						−0.004	−0.192 *	−0.153	−0.066	0.019	0.045
	(0.091)						(0.044)	(0.098)	(0.095)	(0.054)	(0.042)	(0.131)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1176	1176	1176	420	420	420	336	336	336	420	420	420

Note: Values in parentheses are standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Conditional β-convergence results under the geographic distance weight matrix.

	Overall			Eastern			Central			Western		
Model	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**	**KL_Sem**	**KC_Sem**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sar**
β	−0.117 ***	−0.107 ***	−0.242 ***	−0.052 ***	−0.084 ***	−0.310 ***	−0.234 ***	−0.225 ***	−0.276 ***	−0.214 ***	−0.127 ***	−0.305 ***
	(0.013)	(0.013)	(0.017)	(0.015)	(0.019)	(0.035)	(0.038)	(0.037)	(0.037)	(0.034)	(0.025)	(0.030)
ρ	−0.431 ***	−0.288 ***	−0.009			−0.200 *	−0.051	−0.656 ***	−0.141	0.015	0.350 ***	−0.671 ***
	(0.117)	(0.112)	(0.103)			(0.103)	(0.085)	(0.100)	(0.098)	(0.086)	(0.068)	(0.134)
λ				−0.433 ***	−0.588 ***							
				(0.108)	(0.105)							
φ	−0.290 ***	−0.241 ***	0.118			−0.403 ***	−0.231 ***	−0.283 **	−0.226 *	−0.340 ***	−0.125	
	(0.094)	(0.086)	(0.127)			(0.152)	(0.088)	(0.127)	(0.120)	(0.102)	(0.079)	
PerGDP	0.331 ***	0.411 ***	−0.053	0.192	0.378 *	−0.023	−0.065	0.147	0.094	0.508 ***	0.403 **	0.041
	(0.095)	(0.103)	(0.065)	(0.146)	(0.211)	(0.119)	(0.280)	(0.241)	(0.165)	(0.174)	(0.199)	(0.161)
Industrial structure	−0.189 ***	−0.144 **	0.021	−0.135 **	−0.173 **	−0.028	−0.367	−0.181	0.018	−0.156	0.079	−0.149
	(0.058)	(0.063)	(0.041)	(0.061)	(0.085)	(0.046)	(0.247)	(0.181)	(0.126)	(0.102)	(0.125)	(0.094)
Infras	−0.087 **	−0.035	0.130 ***	−0.051	−0.055	0.172 ***	−0.222	0.012	0.251 ***	0.002	−0.014	0.438 ***
	(0.044)	(0.047)	(0.031)	(0.052)	(0.070)	(0.036)	(0.150)	(0.113)	(0.081)	(0.128)	(0.150)	(0.121)
Fiscal	−0.127 *	0.008	0.084 *	0.031	0.209	0.063	0.012	0.186	0.024	−0.492 ***	−0.216	0.278 **
	(0.067)	(0.072)	(0.047)	(0.096)	(0.138)	(0.072)	(0.155)	(0.127)	(0.088)	(0.165)	(0.149)	(0.116)
Urban	0.035	0.014	−0.078 ***	0.016	0.018	−0.079 **	0.068	−0.033	−0.106 ***	0.136 **	0.058	−0.133 ***
	(0.035)	(0.038)	(0.025)	(0.046)	(0.063)	(0.032)	(0.068)	(0.059)	(0.041)	(0.054)	(0.062)	(0.050)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1176	1176	1176	420	420	420	336	336	336	420	420	420

Note: Values in parentheses are standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Absolute β-convergence results under the economic distance weight matrix.

	Overall			Eastern			Central			Western		
Model	**KL_Sdm**	**KC_Sar**	**LC_Sar**	**KL_Sem**	**KC_Sem**	**LC_Sem**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**	**KL_Sdm**	**KC_Sdm**	**LC_Sdm**
β	−0.073 ***	−0.073 ***	−0.219 ***	−0.027 **	−0.058 ***	−0.176 ***	−0.103 ***	−0.151 ***	−0.189 ***	−0.067 *	−0.094 ***	−0.355 ***
	(0.011)	(0.011)	(0.017)	(0.012)	(0.016)	(0.030)	(0.033)	(0.029)	(0.032)	(0.034)	(0.022)	(0.036)
ρ	−0.131 **	−0.122 **	−0.114 **				−0.097	−0.367 ***	−0.238 ***	−0.032	0.175 ***	−0.474 ***
	(0.053)	(0.053)	(0.051)				(0.062)	(0.065)	(0.070)	(0.073)	(0.065)	(0.071)

Table 6. *Cont.*

Model	Overall KL_Sdm	Overall KC_Sar	Overall LC_Sar	Eastern KL_Sem	Eastern KC_Sem	Eastern LC_Sem	Central KL_Sdm	Central KC_Sdm	Central LC_Sdm	Western KL_Sdm	Western KC_Sdm	Western LC_Sdm
λ				−0.433 ***	−0.391 ***	−0.132						
				(0.081)	(0.082)	(0.085)						
φ	−0.000						0.031	−0.096 *	−0.071	−0.132 ***	0.009	−0.399 ***
	(0.032)						(0.032)	(0.056)	(0.058)	(0.048)	(0.039)	(0.084)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1176	1176	1176	420	420	420	336	336	336	420	420	420

Note: Values in parentheses are standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Conditional β-convergence results under the economic distance weight matrix.

Model	Overall KL_Sdm	Overall KC_Sdm	Overall LC_Sdm	Eastern KL_Sem	Eastern KC_Sem	Eastern LC_Sdm	Central KL_Sdm	Central KC_Sdm	Central LC_Sdm	Western KL_Sdm	Western KC_Sdm	Western LC_Sar
β	−0.099 ***	−0.120 ***	−0.241 ***	−0.051 ***	−0.094 ***	−0.341 ***	−0.172 ***	−0.198 ***	−0.280 ***	−0.119 ***	−0.132 ***	−0.257 ***
	(0.012)	(0.014)	(0.017)	(0.016)	(0.020)	(0.036)	(0.036)	(0.034)	(0.037)	(0.024)	(0.026)	(0.031)
ρ												
	−0.146 ***	−0.176 ***	−0.114 **			−0.272 ***	−0.154 **	−0.371 ***	−0.254 ***	−0.050	0.120 *	0.087
λ	(0.053)	(0.053)	(0.052)			(0.090)	(0.064)	(0.065)	(0.071)	(0.073)	(0.069)	(0.060)
				−0.445 ***	−0.397 ***							
φ				(0.084)	(0.086)							
β	−0.046	−0.192 ***	−0.013			−0.266 **	−0.049	−0.120 *	−0.125 *	−0.205 ***	−0.153 **	
	(0.038)	(0.047)	(0.047)			(0.111)	(0.056)	(0.065)	(0.075)	(0.068)	(0.076)	
PerGDP	0.323 ***	0.408 ***	−0.096	0.158	0.334	0.069	0.202	0.597 **	0.500 ***	0.315 ***	0.329	−0.079
	(0.096)	(0.104)	(0.065)	(0.144)	(0.216)	(0.092)	(0.221)	(0.281)	(0.182)	(0.120)	(0.200)	(0.103)
Industrial structure	−0.193 ***	−0.097 *	0.045	−0.065	−0.080	−0.004	−0.356 *	−0.262 *	0.066	−0.168 **	0.084	0.202 **
	(0.056)	(0.059)	(0.039)	(0.056)	(0.081)	(0.043)	(0.207)	(0.159)	(0.101)	(0.077)	(0.119)	(0.085)
Infras	−0.111 ***	−0.097 **	0.102 ***	−0.038	−0.033	0.180 ***	−0.045	0.108	0.311 ***	0.077	−0.034	0.077
	(0.041)	(0.044)	(0.029)	(0.050)	(0.069)	(0.035)	(0.130)	(0.111)	(0.075)	(0.098)	(0.152)	(0.101)
Fiscal	−0.097	0.033	0.114 **	−0.042	0.159	0.024	−0.119	−0.088	−0.283 ***	−0.060	−0.238	0.404 ***
	(0.064)	(0.069)	(0.045)	(0.093)	(0.137)	(0.065)	(0.142)	(0.120)	(0.086)	(0.054)	(0.166)	(0.134)
Urban	0.069 *	0.065 *	−0.075 ***	0.071	0.118 *	−0.067 **	0.070	0.081	−0.041	0.043	0.058	−0.008
	(0.036)	(0.038)	(0.025)	(0.049)	(0.069)	(0.031)	(0.070)	(0.054)	(0.035)	(0.042)	(0.060)	(0.037)
Time	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1176	1176	1176	420	420	420	336	336	336	420	420	420

Note: Values in parentheses are standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

7. Discussion

To improve readability and facilitate comparison across empirical analyses, Table 8 summarizes the key findings regarding the direction, regional disparities, dynamic evolution, and spatial convergence of biased technological change in Chinese agriculture under land constraints.

The findings suggest that biased technological change is closely associated with improvements in land-related productivity under increasing land constraints. As opportunities for farmland expansion become limited, agricultural growth in China has increasingly relied on labor- and capital-augmenting technological pathways to sustain output. This shift reflects a transition from land-dependent growth toward productivity improvement through factor substitution and more intensive use of existing land resources.

Table 8. Summary of main findings.

Dimension	Main Findings	Evidence	Implications for Land-Related Productivity and Agricultural Adaptation
Direction of technological change	Agricultural technological progress in China is predominantly labor-biased, with labor–land bias showing the strongest and continuously increasing tendency.	The average bias indices indicate persistent labor orientation; labor–land bias rises most significantly.	Agricultural growth increasingly relies on improving labor-related and land-related productivity rather than expanding farmland, reflecting adaptation to land scarcity.
Regional heterogeneity	Significant regional differences exist in technology direction choices. Eastern China shows stronger capital-related bias, while central and western regions exhibit different bias patterns.	Regional bias indices differ substantially across eastern, central, and western China.	Heterogeneous resource endowments and farmland constraints induce differentiated pathways of land-related productivity improvement.
Overall regional disparities (Dagum decomposition)	Regional disparities in technological bias continue to widen; transvariation density and interregional differences are major sources.	Gini coefficients rise over time, with different dominant contributors across bias indices.	Uneven changes in factor efficiency may reinforce regional differences in land utilization capacity.
Intraregional disparities	Intraregional differences generally expand in eastern and central regions but fluctuate in western China.	Eastern region exhibits the largest growth in internal disparities.	Land-related productivity improvements remain uneven within regions.
Interregional disparities	Disparities are largest between eastern and western China, especially for capital–land and labor–land bias.	East–west gaps exceed east-central gaps in most indices.	Unequal technological pathways may widen differences in agricultural adaptation to land constraints.
Distributional dynamics (Kernel density)	Most bias indices exhibit right-skewed distributions and weak polarization. Some disparities narrow over time.	Kernel density curves show shortening tails and limited multimodality.	High-productivity provinces remain concentrated, but partial convergence in land-related efficiency emerges.
σ-convergence	No clear σ-convergence exists nationally or regionally.	Coefficients of variation generally increase or fluctuate upward.	Regional differences in technology direction choices persist over time.
Absolute β-convergence	Significant absolute β-convergence exists for all bias indices. Convergence is fastest for labor–land bias.	β coefficients are significantly negative.	Provinces with initially lower land-related productivity tend to catch up over time.
Conditional β-convergence	Conditional β-convergence exists and occurs faster than absolute convergence.	Convergence remains significant after controlling for structural factors.	Economic development, infrastructure, urbanization, and fiscal support affect long-term adjustments in land-related productivity.
Overall implication	Agricultural technological bias reflects differentiated changes in factor productivity under land constraints and exhibits persistent regional heterogeneity with gradual convergence.	Combined evidence from measurement, disparity decomposition, distribution dynamics, and convergence analysis.	Improving food security under farmland constraints increasingly depends on optimizing technology direction choices rather than expanding cultivated land.

However, improvements in land use efficiency remain uneven across regions. Developed regions, with stronger capital accumulation, infrastructure, and innovation capacity, are generally better able to adopt technology pathways that enhance land productivity. By contrast, less-developed regions face structural constraints that slow technological upgrading, contributing to persistent regional disparities despite evidence of gradual convergence.

These differences are shaped not only by resource endowments but also by institutional conditions. In China, the Household Responsibility System, strict farmland protection policies, and uneven regional development have influenced factor allocation and technology adoption in distinctive ways. Such institutional arrangements may partly explain the persistent heterogeneity observed in agricultural technological bias and land-related productivity.

Although this study focuses on China, some findings may have broader relevance for other emerging economies facing land scarcity, structural transformation, and food security pressure. The tendency for agricultural systems to rely increasingly on non-land inputs under constrained farmland conditions may represent a more general adaptation pattern. Nevertheless, the magnitude and evolution of regional disparities are likely to depend on country-specific institutions, land tenure systems, and development strategies.

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Overall, improving food security under land constraints depends not only on technological progress itself, but also on whether technology direction choices are aligned with local resource conditions and supported by appropriate institutional arrangements.

8. Conclusions and Implications

This study investigates the regional disparities, temporal dynamics, and spatial convergence of biased technological change in Chinese agriculture under increasing land constraints. The findings suggest that agricultural adaptation to farmland scarcity increasingly depends on changes in technology direction rather than expansion of cultivated land. In particular, agricultural technological progress has gradually shifted toward labor- and capital-related productivity improvement, reflecting a transition from land-dependent growth toward more intensive use of existing resources. Such changes imply that improvements in land use efficiency are increasingly achieved through differentiated factor adjustment and technological substitution.

At the same time, technological bias exhibits substantial regional heterogeneity and long-term persistence. Differences in resource endowments, development conditions, and infrastructure shape distinct technological pathways across regions, resulting in uneven improvements in land-related productivity. Although convergence tendencies exist, particularly after accounting for structural conditions, regional disparities remain evident. This suggests that agricultural systems tend to adapt to land constraints through region-specific trajectories rather than uniform technological evolution.

These findings indicate that improving food security under limited farmland conditions depends not only on technological progress itself, but also on whether technology direction choices are aligned with local resource conditions and supported by appropriate institutional environments. Therefore, policies aimed at enhancing agricultural sustainability should place greater emphasis on differentiated technological development, rather than relying solely on input expansion or generalized innovation strategies.

From a policy perspective, regional heterogeneity should be fully considered in agricultural technology and land-use policies. Regions with stronger innovation capacity may focus on improving the efficiency of capital-intensive and technology-intensive agriculture, whereas less-developed regions require greater support in infrastructure, technology diffusion, and human capital development to strengthen adaptive capacity under land constraints. In addition, reducing barriers to interregional factor mobility and promoting the diffusion of land-saving technologies may help narrow disparities in land-related productivity. Given the importance of structural conditions in shaping long-term technological trajectories, policy interventions should also improve institutional environments, optimize resource allocation, and support sustainable intensification to balance farmland protection with agricultural growth.

Overall, the experience of China suggests that sustaining agricultural production under increasing land scarcity requires not only technological advancement, but also adaptive technological pathways and institutional arrangements that enhance land use efficiency. Although the empirical analysis focuses on China, these findings may provide broader implications for other emerging economies facing similar challenges of farmland constraints and food security pressure.

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Conflicts of Interest: The authors declare no conflicts of interest.

Notes

1. https://news.qq.com/rain/a/20251016A01WGC00 (accessed on 11 March 2026).
2. https://www.12371.cn/2025/06/25/ARTI1750838275799534.shtml (accessed on 11 March 2026).
3. Due to space constraints, the detailed derivation process has been omitted.
4. Due to space limitations, the detailed derivation is omitted.

References

1. Artamonova, I.; Baturina, I.; Mikhajluk, O.; Poverinova, E. Improving methodologies of assessing the efficiency of agricultural land use. In *Proceedings of the Ecological-Socio-Economic Systems: Models of Competition and Cooperation (ESES 2019)*; Atlantis Press: Paris, France, 2020; pp. 121–124.
2. Zhou, X.; Chen, T.; Zhang, B. Research on the impact of digital agriculture development on agricultural green total factor productivity. *Land* **2023**, *12*, 195. [CrossRef]
3. Lin, L.; Gu, T.; Shi, Y. The influence of new quality productive forces on high-quality agricultural development in China: Mechanisms and empirical testing. *Agriculture* **2024**, *14*, 1022. [CrossRef]
4. Huang, Q.; Guo, W.; Wang, Y. A study of the impact of new quality productive forces on agricultural modernization: Empirical evidence from China. *Agriculture* **2024**, *14*, 1935. [CrossRef]
5. Lei, X.; Zhao, W.; Du, H. Study on the impact of new quality productive forces on agricultural green production efficiency. *Sci. Rep.* **2025**, *15*, 20652. [CrossRef]
6. Zhao, Q.; Bao, H.X.; Zhang, Z. Off-farm employment and agricultural land use efficiency in China. *Land Use Policy* **2021**, *101*, 105097. [CrossRef]
7. Fei, R.; Lin, Z.; Chunga, J. How land transfer affects agricultural land use efficiency: Evidence from China's agricultural sector. *Land Use Policy* **2021**, *103*, 105300. [CrossRef]
8. Yang, X.; Li, X.; Zhong, C. Trends and Determinants of Biased Technological Progress in Chinese Industry. *J. Quant. Tech. Econ.* **2019**, *36*, 101–119. (In Chinese)
9. Li, X.; Li, X. Measurement and Multiple-Effect Decomposition of Total Factor Productivity Evolution in China: A Perspective of Biased Technological Progress. *Econ. Res. J.* **2022**, *57*, 91–208. (In Chinese)
10. Kuang, Y.-P.; Yang, J.-L.; Abate, M.-C. Farmland transfer and agricultural economic growth nexus in China: Agricultural TFP intermediary effect perspective. *China Agric. Econ. Rev.* **2022**, *14*, 184–201. [CrossRef]
11. Volkov, S.; Fomin, A. Provision of effective regulation of land relation and efficient agricultural land use. *Int. Agric. J.* **2018**, 64–71.
12. Ruttan, V.W.; Hayami, Y. Toward a theory of induced institutional innovation. *J. Dev. Stud.* **1984**, *20*, 203–223. [CrossRef]
13. Quaye, A.K.; Hall, C.A.; Luzadis, V.A. Agricultural land use efficiency and food crop production in Ghana. *Environ. Dev. Sustain.* **2010**, *12*, 967–983. [CrossRef]
14. Alston, J.M.; Pardey, P.G. Market distortions and technological progress in agriculture. *Technol. Forecast. Soc. Change* **1993**, *43*, 301–319. [CrossRef]
15. Hu, J.; Wang, Z.; Huang, Q. Factor allocation structure and green-biased technological progress in Chinese agriculture. *Econ. Res. Ekon. Istraživanja* **2021**, *34*, 2034–2058. [CrossRef]
16. Han, H.; Li, H.; Zhao, L. Determinants of factor misallocation in agricultural production and implications for agricultural supply-side reform in China. *China World Econ.* **2018**, *26*, 22–42. [CrossRef]
17. Acemoglu, D. Directed technical change. *Rev. Econ. Stud.* **2002**, *69*, 781–809. [CrossRef]
18. Acemoglu, D. Localised and biased technologies: Atkinson and Stiglitz's new view, induced innovations, and directed technological change. *Econ. J.* **2015**, *125*, 443–463. [CrossRef]
19. Klump, R.; McAdam, P.; Willman, A. Factor Substitution and Factor-Augmenting Technical Progress in the United States: A Normalized Supply-Side System Approach. *Rev. Econ. Stat.* **2007**, *89*, 183–192. [CrossRef]
20. Yang, Z.; Shao, S.; Yang, L.; Miao, Z. Improvement pathway of energy consumption structure in China's industrial sector: From the perspective of directed technical change. *Energy Econ.* **2018**, *72*, 166–176. [CrossRef]

21. Wang, J.; Jiao, Y.; Jiang, S. Regional Disparities and Dynamic Evolution of the Direction of Technological Progress in China's Eight Comprehensive Economic Regions: 1978–2017. *J. Quant. Tech. Econ.* **2021**, *38*, 3–21. (In Chinese)
22. Li, Z.; Li, D.; Yang, W.; Qi, X. The spatial-temporal evolution and spatial convergence of ecological total factor productivity in China. *Energy Environ.* **2022**, *33*, 617–639. (In Chinese) [CrossRef]
23. Yang, W.; Yu, X.; Wang, D.; Yang, J.; Zhang, B. Spatio-temporal evolution of technology flows in China: Patent licensing networks 2000–2017. *J. Technol. Transf.* **2021**, *46*, 1674–1703. [CrossRef]
24. Le'on-Ledesma, M.A.; McAdam, P.; Willman, A. Production technology estimates and balanced growth. *Oxf. Bull. Econ. Stat.* **2015**, *77*, 40–65. [CrossRef]
25. Yu, W.; Zhang, P.; Ji, Z. Regional Disparities, Distribution Dynamics, and Convergence of Ecological Efficiency in Chinese Urban Agglomerations. *J. Quant. Tech. Econ. (Chin.)* **2021**, *38*, 23–42. (In Chinese)
26. Zhang, J.; Liu, Y.; Zhang, E.; Chen, J.; Tan, Q. Dynamics and driving mechanisms of cultivated land at county level in China. *Acta Geogr. Sin.* **2023**, *78*, 2105–2127.
27. Yin, Q.; Sui, X.; Ye, B.; Zhou, Y.; Li, C.; Zou, M.; Zhou, S. What role does land consolidation play in the multi-dimensional rural revitalization in China? A research synthesis. *Land Use Policy* **2022**, *120*, 106261. [CrossRef]
28. Zhang, W.; Wang, B.; Wang, J.; Wu, Q.; Wei, Y.D. How does industrial agglomeration affect urban land use efficiency? A spatial analysis of Chinese cities. *Land Use Policy* **2022**, *119*, 106178. [CrossRef]
29. Li, X.; Li, X. Biased Technological Progress and China's Industrial Total Factor Productivity Growth. *Econ. Res.* **2018**, *53*, 82–96. (In Chinese)
30. Korinek, A.; Stiglitz, J.E. *Steering Technological Progress*; National Bureau of Economic Research: Cambridge, MA, USA, 2026.
31. Antonelli, C.; Feder, C.; Quatraro, F. *Directed Technological Change and Technological Congruence: A New Framework for the Smart Specialization Strategy*; University of Turin: Turin, Italy, 2018.
32. Antonelli, C.; Feder, C. A long-term comparative analysis of the direction and congruence of technological change. *Socio-Econ. Rev.* **2019**, *19*, 583–605. [CrossRef]
33. Greaker, M.; Heggedal, T.R.; Rosendahl, K.E. Environmental policy and the direction of technical change. *Scand. J. Econ.* **2018**, *120*, 1100–1138. [CrossRef]
34. Deng, X.; Liang, L.; Wu, F.; Wang, Z.; He, S. A review of the balance of regional development in China from the perspective of development geography. *J. Geogr. Sci.* **2022**, *32*, 3–22. [CrossRef]
35. Acemoglu, D.; Akcigit, U.; Kerr, W. Networks and the macroeconomy: An empirical exploration. *Nber Macroecon. Annu.* **2016**, *30*, 273–335. [CrossRef]
36. Ertur, C.; Koch, W. Growth, technological interdependence and spatial externalities: Theory and evidence. *J. Appl. Econom.* **2007**, *22*, 1033–1062. [CrossRef]
37. Inklaar, R.; Diewert, W.E. Measuring industry productivity and cross-country convergence. *J. Econom.* **2016**, *191*, 426–433. [CrossRef]
38. Antonelli, C.; Scellato, G. Firms size and directed technological change. *Small Bus. Econ.* **2015**, *44*, 207–218. [CrossRef]
39. Zhou, X.; Ma, W. Agricultural mechanization and land productivity in China. *Int. J. Sustain. Dev. World Ecol.* **2022**, *29*, 530–542. [CrossRef]
40. León-Ledesma, M.A.; McAdam, P.; Willman, A. Identifying the Elasticity of Substitution with Biased Technical Change. *Am. Econ. Rev.* **2010**, *100*, 1330–1357. [CrossRef]
41. Zhou, Y.; Li, W.; Li, H.; Wang, Z.; Zhang, B.; Zhong, K. Impact of water and land resources matching on agricultural sustainable economic growth: Empirical analysis with spatial spillover effects from Yellow River Basin, China. *Sustainability* **2022**, *14*, 2742. [CrossRef]
42. Li, G. China's Green Productivity Revolution in Agriculture: 1978–2008. *China Econ. Q.* **2014**, 537–558. (In Chinese)
43. Wang, L.; Yuan, L. Factor Endowment, Biased Technological Progress, and the Structure of Factor Income Distribution in China's Agricultural Sector. *J. Northeast. Norm. Univ. (Philos. Soc. Sci. Ed.)* **2015**, *29*, 70–80. (In Chinese)
44. Wang, L.; Yuan, L. Biased Technological Progress, Industrial Structure Transformation, and the Pattern of Factor Income Distribution in China. *Econ. Res. J.* **2018**, *53*, 115–131. (In Chinese)
45. Hayami, Y.; Ruttan, V.W. *Agricultural Development: An International Perspective*; The Johns Hopkins Press: Baltimore, MD, USA; London, UK, 1971.

46. Zhu, H.; Geng, C.; Chen, Y. Urban–rural integration and agricultural technology innovation: Evidence from China. *Agriculture* **2024**, *14*, 1906. [CrossRef]
47. Bruno, R.L.; Douarin, E.; Korosteleva, J.; Radosevic, S. Technology choices and growth: Testing new structural economics in transition economies. *J. Econ. Policy Reform* **2015**, *18*, 131–152. [CrossRef]

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