

Measuring Green Total Factor Productivity Growth in China's Agricultural Sector: A CO₂ Adjusted Growth Accounting Approach

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Abstract: This study examines agricultural productivity growth in China from 2013 to 2021 using a CO₂-adjusted growth-accounting framework. Agricultural value-added growth is decomposed into capital, labor, and residual productivity components, and conventional total factor productivity (TFP) growth is adjusted for changes in CO₂ intensity. The analysis uses national agricultural data and compares conventional and CO₂-adjusted TFP growth across annual and period-level changes. The results show substantial variation in productivity growth over the study period. Traditional TFP growth averaged 2.90% in 2013–2014, 5.08% in 2015–2017, and 5.19% in 2018–2021. Capital contributed positively to output growth in the first and third periods, whereas labor contributions remained small and negative. Over 2012–2021, agricultural value added increased by 58.60%, while labor input and CO₂ emissions declined by 41.70% and 25.30%, respectively. Cumulative traditional TFP growth was 51.90%, compared with 57.40% for CO₂-adjusted TFP. The environmental adjustment became positive in the later years and reached 2.65 percentage points in 2020, when CO₂ emissions fell by 22.10% while agricultural value added increased by 9.82%. Sensitivity analysis shows that the unusually high TFP growth in 2016 affects the magnitude of average productivity growth but has little effect on the average CO₂-based adjustment. The findings highlight the importance of incorporating environmental changes into agricultural productivity measurement while recognizing that the CO₂ adjustment represents an accounting relationship rather than a causal effect.

Keywords: Agricultural Productivity; Green TFP; Growth Accounting; CO₂ Emissions; CO₂ Intensity

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1. Introduction

As China pursues high-quality development and carbon neutrality, its agricultural sector faces mounting pressure to improve productivity while reducing environmental impacts. China has also established a national policy framework for achieving carbon peaking and carbon neutrality, reinforcing the need to reconcile economic development with environmental sustainability^[1]. China's agricultural greenhouse gas emissions include not only carbon dioxide (accounting for 10% to 15%), but also non-carbon dioxide greenhouse gases such as methane (45% to 55%) and nitrous oxide (30% to 40%)^[2]. Agriculture remains one of the largest sources of greenhouse gas (GHG) emissions in China, particularly due to fertilizer overuse, livestock waste, and inefficient land use^[3]. However, conventional Total Factor Productivity (TFP) measures fail to reflect the

environmental costs of such growth, potentially overstating real productivity^[4].

Traditional assessments of agricultural performance have largely relied on measures of output growth or total factor productivity (TFP). In the neoclassical growth framework, TFP captures the portion of output growth not explained by observable factor inputs and is commonly interpreted as a proxy for technological progress or efficiency improvement^[5]. However, conventional TFP measures implicitly assume that all outputs are desirable and that production activities generate no environmental externalities. In sectors such as agriculture, where economic output is closely intertwined with pollution emissions, this assumption may lead to a systematic overestimation of true productivity performance^{[4][6]}.

To address this limitation, an influential strand of literature has incorporated environmental factors into productivity measurement. Färe et al. (1994)^[7] established an important foundation for productivity measurement using the Malmquist productivity index, while Chung et al. (1997)^[8] extended the framework to incorporate undesirable outputs through the Malmquist–Luenberger productivity index. Subsequent studies further refined this approach using directional distance functions and slack-based measures to evaluate environmentally adjusted productivity and eco-efficiency^{[8][9]}. Empirical applications of these models have demonstrated that once environmental costs are internalized, productivity growth may be substantially lower than that suggested by conventional measures, particularly in developing economies with energy-intensive growth patterns^[10].

In the context of China's agricultural sector, a growing body of literature has adopted non-parametric frontier methods—such as DEA-based Malmquist indices, SBM efficiency models, and directional distance function approaches—to assess green productivity or eco-efficiency. These studies have generated valuable insights into regional disparities, technological gaps, and environmental efficiency levels^{[11][12]}. However, frontier-based methods are primarily designed to evaluate relative efficiency against a best-practice benchmark and are less informative in explaining the underlying sources of productivity change. DEA-based indices do not provide an explicit decomposition of output growth into factor accumulation, environmental burden, and residual productivity, which limits their interpretability from a macroeconomic and policy evaluation perspective. For example, Liu et al. (2021)^[13] employed a Super-SBM model to measure China's agricultural GTFP while explicitly incorporating carbon emissions, whereas Chen et al. (2021)^[14] incorporated both agricultural non-point source pollution and CO₂ emissions into a three-stage SBM-DEA framework. These studies illustrate how environmental factors can be incorporated into frontier-based agricultural productivity assessment^{[9][14]}. An alternative approach is to incorporate environmental factors directly into the growth-accounting framework, as proposed by Xepapadeas et al. (2007)^[15]. This approach allows environmental use to be accounted for as a component of output growth rather than solely as an undesirable output in a production frontier.

This study addresses this gap by applying a CO₂-weighted growth accounting framework to examine the evolution of traditional and CO₂-adjusted TFP growth in China's agricultural sector from 2013 to 2021. The framework decomposes agricultural value-added growth into capital and labor contributions and introduces a CO₂-based environmental adjustment to obtain a CO₂-adjusted TFP residual. The analysis further compares the results across three analytical periods to examine changes in the relative contributions of factor accumulation, environmental adjustment, and residual productivity growth. In doing so, the study provides a transparent accounting framework for assessing changes in agricultural productivity under increasing environmental constraints.

the battle for the “greatest player” in basketball history.

2. Literature Review

2.1 Theoretical Foundations of Environmental Productivity Measurement

Total factor productivity (TFP) has long been used to characterize productivity growth and technical change beyond the contribution of measured factor inputs^{[4][5]}. Within the growth-accounting framework, output growth can be decomposed into the contributions of factor accumulation and a residual component representing productivity growth^[16]. However, Traditional TFP measures generally focus on economic outputs and factor inputs without explicitly incorporating environmental externalities. As a result, they may provide an incomplete or potentially biased assessment of productivity change when environmental performance changes substantially^[17]. To address this shortcoming, Färe et al. (1994)^[7] developed the

nonparametric Malmquist productivity framework for measuring productivity change and decomposing it into efficiency and technical change. Subsequently, Chung et al. (1997)^[8] extended this framework by introducing the Malmquist–Luenberger productivity index, which explicitly incorporates undesirable outputs into productivity measurement.

Further supporting this paradigm shift, Zhou et al. (2008)^[18] provided a comprehensive review of Data Envelopment Analysis (DEA) in energy and environmental studies, highlighting the rising importance of non-desirable outputs in evaluating efficiency. Their work underscores that measuring productivity without environmental considerations is both theoretically incomplete and policy-informative misleading.

2.2 Empirical Evidence from Developing Economies

Recent empirical studies have emphasized the importance of internalizing environmental externalities in productivity measurements, particularly in the context of developing economies. For example, Elsadig (2012)^[19] examined green TFP in East Asia and found that increased environmental intensity significantly reduced long-term productivity growth. This indicates that economic growth strategies that ignore environmental costs are ultimately unsustainable.

Similarly, Rusiawan et al. (2015)^[10] conducted a pioneering study on Indonesia using a CO₂-weighted growth accounting approach. Their results revealed that Indonesia's green TFP averaged –1.83% annually from 1976 to 2010, significantly lower than conventional TFP estimates. This finding suggests that when carbon emissions are accounted for, the true productivity performance of carbon-intensive economies may be overestimated. These studies highlight the necessity of integrating environmental factors into productivity frameworks, not only from a theoretical perspective but also for informing policy in carbon-constrained development contexts.

2.3 Agricultural GTFP in China: Regional Disparities and Emission Accounting

Recent Chinese studies have increasingly examined the determinants and drivers of agricultural green total factor productivity. For example, Chen et al. (2023)^[21] examined the relationship between the digital economy, green technology innovation, and agricultural green total factor productivity, illustrating the growing interest in the drivers of agricultural green productivity beyond the measurement of productivity themselves.

In recent years, the measurement of agricultural GTFP in China has evolved rapidly, driven by data improvements and methodological advancements. Liu, Zhu, and Wang (2021)^[20] employed a Super-SBM model to estimate GTFP across 31 provinces from 2003 to 2017. Their analysis revealed an overall upward trend in GTFP, though with strong regional heterogeneity—eastern provinces consistently outperformed central and western counterparts. Moreover, fertilizer use was identified as the dominant source of agricultural carbon emissions.

Building on this, Xu et al. (2019)^[22] constructed a Global Malmquist-Luenberger index based on a more granular carbon inventory covering five sources: rice cultivation, fertilizer, cropland soil, livestock, and straw burning. Using data from 1998 to 2016, they found that green TFP improved fastest in eastern regions (4.2% annually), followed by the central (3.4%) and western (2.5%) regions. Their results also showed that green technological change—not efficiency improvement—was the main driver of TFP gains.

At the micro level, Xu et al. (2025)^[23] investigated smallholder farm performance from 2018 to 2022 using Life Cycle Assessment and Super-SBM models. They found that although green TFP increased by 7.7%, greenhouse gas emission intensity (GEI) rose by 12.2% during the same period. Fertilizer overuse was the primary contributor, and resource misallocation—especially of capital and land—was a major constraint on further improvement.

These studies collectively highlight the complexity of achieving green productivity growth in agriculture, where environmental and efficiency trade-offs are often interlinked. However, these frontier-based approaches generally focus on relative efficiency and productivity change rather than explicitly accounting for the contributions of individual production factors within a common growth-accounting identity. Consequently, existing studies provide limited evidence regarding how capital accumulation, labor dynamics, and carbon-emission burdens jointly shape the evolution of agricultural green productivity over time. The present study addresses this limitation by introducing a CO₂-weighted growth accounting framework that decomposes agricultural growth into capital, labor, emission, and residual productivity components.

Table 1 summarizes key studies on green total factor productivity, covering the theoretical foundations of productivity

measurement, environmental productivity methods, international applications, and empirical evidence from China's agricultural sector. While early studies established the foundations for productivity decomposition and environmental productivity measurement (Färe et al., 1994; Chung et al., 1997)^{[7][8]}, subsequent research extended these approaches to environmentally adjusted productivity growth, including CO₂-weighted growth accounting (Rusiawan et al., 2015)^[10]. Recent studies in China have mainly employed frontier-based methods to examine regional differences, technological progress, environmental performance, and the determinants of agricultural GTFP. This study complements this literature by applying a CO₂-weighted growth-accounting framework to examine how capital, labor, carbon emissions, and residual productivity contribute to agricultural growth over time.

Table 1. Literature Review on Green Total Factor Productivity

No.	Author	Region / Period	Method	Key Findings	Relevance to This Study
1	Comin (2006) ^[4]	Theoretical	Solow residual / TFP accounting	TFP captures productivity beyond factor accumulation.	Foundation for growth accounting
2	Färe et al. (1994) ^[7]	17 OECD countries (1979–1988)	Malmquist productivity index	Decomposed productivity change into efficiency and technical change.	Foundation for productivity decomposition
3	Chung et al. (1997) ^[8]	Environmental productivity framework	Malmquist–Luenberger index	Incorporated undesirable outputs into productivity measurement.	Foundation for environmental productivity measurement
4	Zhou et al. (2008) ^[18]	Global DEA literature	DEA in energy and environmental studies	Reviewed DEA applications in environmental efficiency analysis.	Context for DEA-based GTFP research
5	Elsadig (2012) ^[19]	East Asia (1990–2009)	CO ₂ -adjusted TFP	Showed that environmental adjustment changes productivity estimates.	Evidence for environmental adjustment
6	Rusiawan et al. (2015) ^[10]	Indonesia (1976–2010)	CO ₂ -weighted growth accounting	Reported differences between conventional and environmentally adjusted productivity.	Closest methodological precedent
7	Liu, Zhu & Wang (2021) ^[13]	China, 31 provinces (2003–2017)	Super-SBM	Found regional differences in agricultural GTFP.	Evidence from Chinese agriculture
8	Xu et al. (2019) ^[22]	China (1998–2016)	GML + emission inventory	Identified technological progress as an important source of GTFP growth.	Illustrates frontier-based GTFP approach
9	Xu et al. (2025) ^[23]	China, smallholder farms (2018–2022)	LCA + Super-SBM	Linked agricultural productivity with environmental burdens at the farm level.	Extends environmental productivity analysis to micro level
10	Chen, Hu & Wu (2023) ^[21]	China (2000–2020)	Panel regression	Digital economy and green innovation were associated with agricultural GTFP.	Illustrates determinants of agricultural GTFP

2.4 Research Gaps and Contributions of This Study

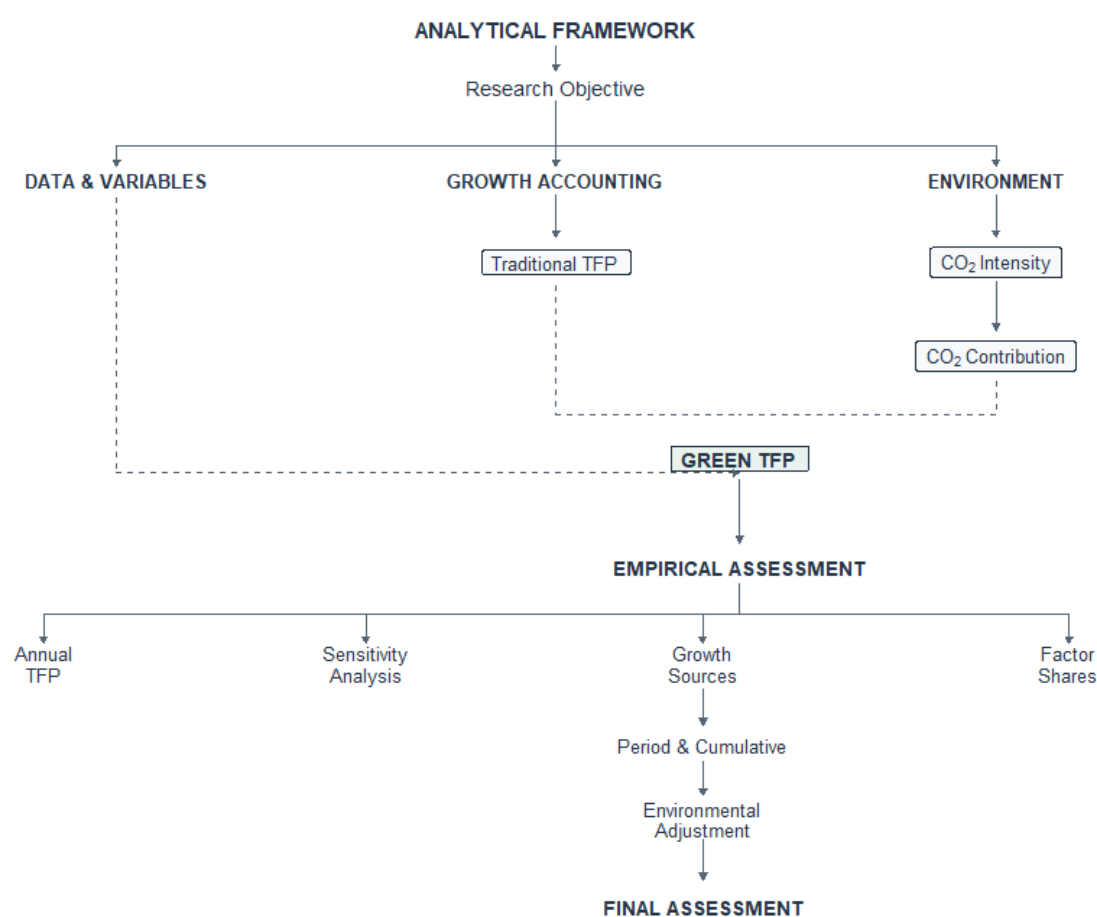
Despite the extensive literature on agricultural green total factor productivity (GTFP), relatively limited attention has been paid to the growth-accounting interpretation of environmentally adjusted productivity growth. Existing studies mainly rely on

frontier-based approaches such as DEA, SBM, and ML/GML indices, which are effective for assessing relative efficiency and productivity change but do not directly decompose aggregate output growth into factor contributions and residual productivity within a growth-accounting identity. This distinction is relevant to China's agricultural sector, where output, capital, labor, and CO₂ emissions have changed substantially over time.

This study applies the CO₂-weighted growth-accounting framework of Rusiawan et al. (2015) to China's agriculture during 2012–2021. It decomposes agricultural output growth into capital, labor, CO₂-related, and residual productivity components and compares conventional TFP with CO₂-adjusted TFP.

The study makes three contributions. First, it extends CO₂-weighted growth accounting to China's agricultural sector from a national aggregate perspective. Second, it complements frontier-based GTFP studies by quantifying the contributions of factor inputs, CO₂ emissions, and residual productivity to output growth. Third, it shows how environmental adjustment changes measured productivity growth over time. The CO₂-adjusted measure is interpreted as an accounting indicator rather than a frontier-based GTFP index or causal estimate. Figure 1 summarizes the analytical framework and empirical research route.

Figure 1. Analytical Framework of the Study



3. Methodology

3.1 Analytical Framework and Model Rationale

This study adopts a growth-accounting framework to decompose agricultural value-added growth into the contributions of capital, labor, and a residual productivity component. Following the Solow (1957)^[5] growth-accounting approach, the residual represents productivity growth not explained by the measured factor inputs. Environmental factors can also be incorporated into this framework to account for the environmental resources associated with production^{[15][24][25]}.

In this study, agricultural CO₂ emissions are incorporated into the conventional TFP residual through a CO₂-intensity-based adjustment. The resulting measure is referred to as CO₂-adjusted TFP growth. This approach provides an aggregate measure of agricultural productivity growth that accounts for changes in CO₂ intensity while retaining the basic structure of

conventional growth accounting.

3.2 Production Function and Traditional TFP Measurement

We assume a standard Cobb-Douglas production function:

$$Y_t = A_t \cdot K_t^{\alpha_K} \cdot L_t^{\alpha_L} \quad (1)$$

where Y denotes agricultural value added (AGDP), K_t represents capital input, L_t denotes labor input, and A_t captures total factor productivity (TFP). The parameters α_K and α_L correspond to the income shares of capital and labor, respectively, and satisfy the constant returns to scale condition:

The log-differentiation of Equation (1) yields the Solow residual :

$$\alpha_K + \alpha_L = 1 \quad (2)$$

Taking natural logarithms of Equation (1) and differentiating with respect to time yields the conventional Solow residual, which measures TFP growth as the portion of output growth not explained by observable factor inputs:

$$gA_t = gY - \alpha_K \cdot gK_t - \alpha_L \cdot gL_t \quad (3)$$

where gY_t , gK_t , and gL_t denote the logarithmic growth rates of output, capital, and labor, respectively. In the empirical analysis, these growth rates are approximated using log differences.

3.3 Measurement of Capital and Labor Inputs

Capital input is proxied by total agricultural machinery power, measured in 10,000 kW. Because comprehensive agricultural capital-stock data is not directly available at the required level of aggregation, agricultural machinery power is used as an observable proxy for agricultural capital input. Labor input is measured by the number of workers employed in the primary sector.

$$K = \text{agricultural machinery total power} \quad (4)$$

$$L = \text{primary sector employment} \quad (5)$$

3.4 Factor Income Shares and Growth Rates

3.4.1 Labor Income Share

The labor income share is calculated as the ratio of total agricultural labor compensation to agricultural value added:

$$LIS_t = \frac{Wage_t}{Y_t} \quad (6)$$

Where $Wage_t$ denotes total labor compensation in the agricultural sector and Y_t denotes agricultural value added. To reduce the sensitivity of the growth-accounting decomposition to year-to-year fluctuations in the observed labor income share, the factor share applied to the decomposition is calculated as the average of the current and preceding year's labor income shares:

$$\alpha_L = \frac{LIS_t + LIS_{t-1}}{2} \quad (7)$$

Under the constant-returns-to-scale assumption, the capital factor share is obtained residually as:

$$\alpha_K = 1 - \alpha_L \quad (8)$$

To reduce the influence of year-to-year fluctuations in the labor income share, the factors used in the growth-accounting decomposition are constructed as the average of the current and preceding year's labor income shares.

3.4.2 Logarithmic Growth Rates

The growth rates of output, capital, labor, and CO₂ emissions are calculated as:

$$gX_t = 100 \cdot (\ln X_t - \ln X_{t-1}) \quad (9)$$

where X_t denotes the relevant variable in period t . Expressing growth rates in percentage terms facilitates comparison across variables and periods.

3.5 Environmental Adjustment of TFP Growth

To incorporate environmental pressure into the conventional growth-accounting framework, agricultural CO₂ emissions are incorporated as an environmental burden associated with agricultural production. Rather than estimating a separate environmental production frontier, this study extends conventional TFP growth by introducing a CO₂-intensity-based accounting adjustment. This formulation follows the broader green growth-accounting perspective developed in the

environmental productivity literature (Tzouvelekas et al., 2006)^[24] and its subsequent empirical application using CO₂-weighted growth accounting^[10]. The CO₂ intensity weight is defined as:

$$\tau_t = \frac{1}{2} \left(\frac{CO2_t}{Y_t} + \frac{CO2_{t-1}}{Y_{t-1}} \right) \quad (10)$$

This term reflects the average CO₂ emissions per unit of output across adjacent periods. It should be noted that τ_t is interpreted as an intensity-based weight, rather than a structural output elasticity derived from production function estimation. Green total factor productivity growth is then calculated as:

$$gA_t^{CO_2} = gY - \alpha k \cdot gK - \alpha L \cdot gL - \tau_t \cdot gCO_2 \quad (11)$$

where $gA_t^{CO_2}$ denotes CO₂-adjusted TFP growth, gY_t is the growth rate of agricultural value added, gK_t and gL_t are the growth rates of capital and labor inputs, respectively, and $gCO_{2,t}$ is the growth rate of agricultural CO₂ emissions. The first three terms correspond to the conventional growth-accounting components, while the final term represents the CO₂-based adjustment.

For comparison, traditional TFP growth is calculated without the CO₂ adjustment:

$$gA_t^{trad} = gY_t - \alpha K_t gK_t - \alpha L_t gL_t \quad (12)$$

Thus, the relationship between traditional and CO₂-adjusted TFP growth can be expressed as:

$$gA_t^{CO_2} = gA_t^{trad} - \tau_t \cdot gCO_2 \quad (13)$$

Accordingly, agricultural value-added growth can be decomposed into capital, labor, CO₂-related, and residual productivity components:

$$gY_t = \alpha K_t gK_t + \alpha L_t gL_t + \tau_t \cdot gCO_2 + gA_t^{CO_2} \quad (14)$$

This decomposition provides an accounting-based breakdown of agricultural value-added growth into factor contributions, the CO₂-related adjustment, and CO₂-adjusted TFP growth.

3.6 Period-wise Averaging and Comparative Analysis

This study divides the observation period into three analytical periods (2013–2014, 2015–2017, and 2018–2021) to summarize changes in the sources of agricultural growth over time. the annual contribution components are averaged across predefined development stages:

$$\bar{X} = \frac{1}{n_s} \sum_{t \in s} X_t \quad (15)$$

where n_s denotes the number of years in stage s . where X_t denotes an annual growth-accounting component and n_s is the number of annual observations in analytical period.

The period-specific averages are calculated for agricultural value-added growth, capital contribution, labor contribution, CO₂-based adjustment, traditional TFP growth, and CO₂-adjusted TFP growth. Specifically,

$$\overline{gY_s} = \frac{1}{n_s} \sum_{t \in s} gY_t = gY_t \quad (16)$$

$$\overline{\alpha k gK_s} = \frac{1}{n_s} \sum_{t \in s} \alpha k * tgK_t \quad (17)$$

$$\overline{\alpha L gL_s} = \frac{1}{n_s} \sum_{t \in s} \alpha L * tgL_t \quad (18)$$

$$\overline{\tau_t \cdot gCO_{2s}} = \frac{1}{n_s} \sum_{t \in s} \tau_t \cdot gCO_{2t} \quad (19)$$

$$\overline{gA_s^{trad}} = \frac{1}{n_s} \sum_{t \in s} gA_t^{trad} \quad (20)$$

$$\overline{gA_s^{CO_2}} = \frac{1}{n_s} \sum_{t \in s} gA_t^{CO_2} \quad (21)$$

where s represents each analytical period: 2013–2014, 2015–2017, and 2018–2021.

3.6.1 On the Use of Stage-wise Averaging and Result Stability.

The period-level averaging is used as a descriptive device to smooth short-term fluctuations and facilitate comparison of

growth components across periods. It does not replace the annual growth-accounting estimates, which remain the basis of the analysis. Pronounced annual fluctuations, particularly in 2016 and 2020, are examined separately in the annual decomposition and sensitivity analysis.

3.7 Variable Definitions

Table 2 summarizes the variables, notation, measurement units, and definitions used in the growth-accounting framework.

Table 2. Variable Definitions and Notations

Symbol	English Name	Unit	Definition
Y	Agricultural value added (AGDP)	100 million yuan	Agricultural value added as the output measure
K	Agricultural machinery power	10,000 kW	Total power of agricultural machinery, used as a proxy for agricultural capital input
L	Primary-sector employment	10,000 persons	Number of workers employed in the primary sector
CO ₂	Agricultural CO ₂ Emissions	10,000 tons	Agricultural CO ₂ emissions used for the CO ₂ -based environmental adjustment
Wage	Agricultural labor compensation	100 million yuan	Total wage payments to agricultural workers
αL	Labor Income Share	Ratio (0–1)	$(LIS + LIS_{t-1})/2$
αK	Capital Income Share	Ratio (0–1)	$1 - \alpha L$
τ	CO ₂ intensity weight	-	$\frac{1}{2}(\frac{CO_2}{Y} + CO_{2,t-1}/Y_{t-1})$
gY	Agricultural Value-Added Growth	%	$100[\ln Y_t - \ln Y_{t-1}]$
gK	Capital Growth Rate	%	$100[\ln K_t - \ln K_{t-1}]$
gL	Labor Growth Rate	%	$100[\ln L_t - \ln L_{t-1}]$
gCO ₂	CO ₂ Growth Rate	%	$100[\ln CO_{2,t} - \ln CO_{2,t-1}]$
K contribution	Capital Contribution	%	$\alpha K \times gK$
L contribution	Labor Contribution	%	$\alpha L \times gL$
CO ₂ adjustment	CO ₂ -Based Adjustment	percentage points	$- \times gCO_2$
TFP _t ^{trad}	Traditional TFP	%	$gY_t - \alpha K - \tau \quad gK_t - \alpha L, \tau \quad gL_t$
TFP _t ^{green}	CO ₂ -Adjusted TFP Growth	%	TFP _t ^{trad} + CO ₂ adjustment

4. Results

4.1 Annual Evolution of Agricultural Productivity

The annual changes indicate substantial year-to-year fluctuations in both traditional TFP and CO₂-adjusted TFP. In 2013, both measures recorded relatively high growth, followed by negative growth in 2014. Productivity recovered to modest growth in 2015 and reached its highest measured growth rate during the sample period in 2016, when traditional TFP and CO₂-adjusted TFP increased by 18.33% and 18.45%, respectively. TFP growth turned negative again in 2017 but subsequently recovered. CO₂-adjusted TFP increased by 3.19% in 2018 and 6.70% in 2019.

A notable difference emerged in 2020. Traditional TFP increased by 7.19%, whereas CO₂-adjusted TFP increased by 9.84%, resulting in a 2.65-percentage-point difference, the largest CO₂-based adjustment observed during the sample period. In the same year, agricultural value added increased by 9.82%, while labor input and CO₂ emissions declined by 16.54% and 22.10%, respectively. Thus, the relatively high growth in CO₂-adjusted TFP in 2020 coincided with output expansion, a reduction in labor input, and a substantial decline in CO₂ emissions. This annual association reflects simultaneous changes

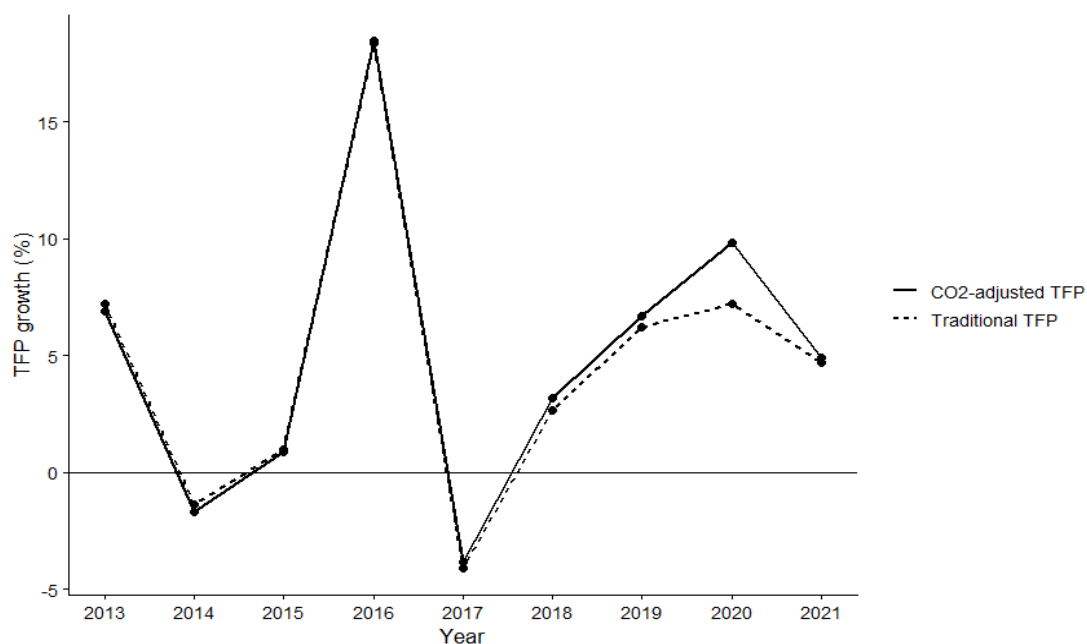
captured by the productivity decomposition and should not be interpreted as evidence that CO₂ reductions themselves caused the increase in CO₂-adjusted TFP. Figure 2 visualizes the annual movements of traditional and CO₂-adjusted TFP growth over 2013–2021. The two measures generally follow similar trends, while their divergence is most pronounced in 2020, when CO₂-adjusted TFP growth exceeded traditional TFP growth by 2.65 percentage points.

Table 3. Annual Traditional and CO₂-Adjusted TFP Growth, 2013–2021

Year	Traditional TFP (%)	CO ₂ -Adjusted TFP Growth (%)	CO ₂ Adjustment (pp)	Interpretation
2013	7.19	6.90	-0.29	Positive productivity growth
2014	-1.40	-1.68	-0.28	Productivity decline
2015	1.00	0.88	-0.12	Slight productivity growth
2016	18.33	18.45	0.120	Pronounced productivity growth
2017	-4.11	-3.81	0.30	Productivity decline
2018	2.67	3.19	0.52	Green productivity exceeds traditional TFP
2019	6.20	6.70	0.50	Green productivity improvement
2020	7.19	9.84	2.65	Largest environmental adjustment
2021	4.72	4.88	0.16	Continued productivity growth

Note: CO₂-adjusted TFP incorporates the CO₂-based environmental adjustment, whereas traditional TFP excludes this adjustment. The first sample year, 2012, is omitted because annual growth rates require lagged observations.

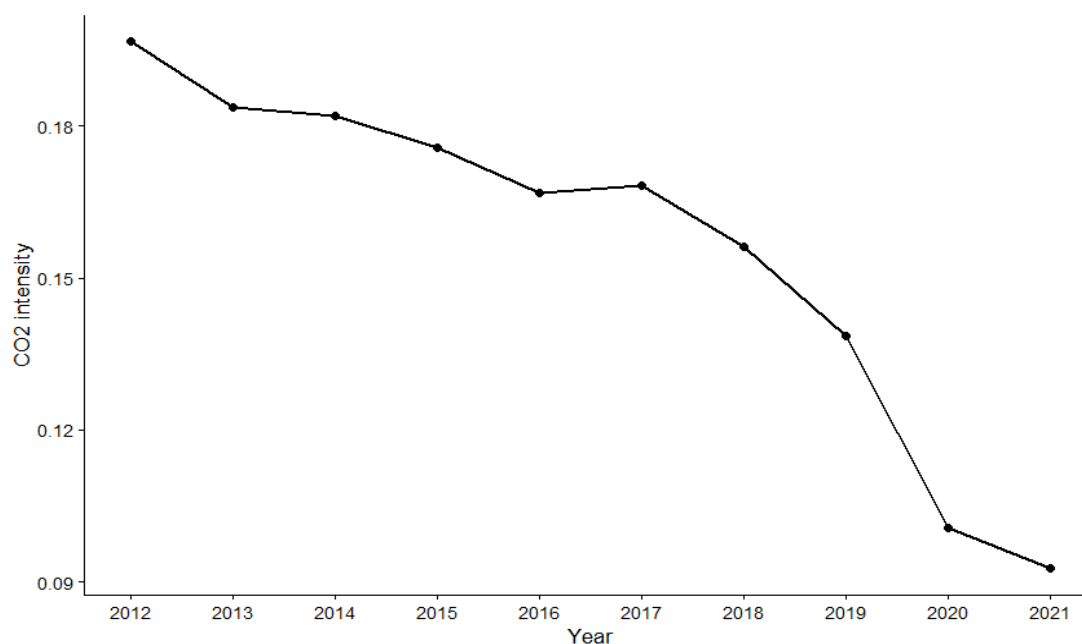
Figure 2. Traditional and CO₂-Adjusted TFP Growth in China's Agriculture, 2013–2021



Agricultural CO₂ intensity also declined substantially over the study period. Measured as CO₂ emissions per 100 million yuan of agricultural value added, CO₂ intensity decreased from 0.197 in 2012 to 0.093 in 2021, representing a 52.90% reduction relative to the 2012 level. The decline was relatively gradual during the early years but became more pronounced after 2017. CO₂ intensity decreased from 0.156 in 2018 to 0.139 in 2019 and then to 0.101 in 2020, before reaching 0.093 in 2021. A temporary increase was observed in 2017, when CO₂ intensity rose slightly from 0.167 to 0.168. Overall, the downward trend indicates that agricultural value added was increasingly generated with lower CO₂ emissions per unit of output.

The sharp reduction in CO₂ intensity in 2020 is particularly notable. CO₂ emissions declined by 22.10%, while agricultural value added increased by 9.82%, resulting in a 31.92% decline in CO₂ intensity relative to the previous year. This coincided with the largest CO₂-based adjustment in the growth-accounting results, with CO₂-adjusted TFP exceeding traditional TFP by 2.65 percentage points. However, this correspondence should be interpreted as an accounting association rather than evidence of a causal relationship. Figure 3 presents the evolution of agricultural CO₂ intensity over 2012–2021.

Figure 3. Evolution of Agricultural CO₂ Intensity in China, 2012–2021



Because the exceptionally high TFP growth observed in 2016 coincided with a substantial decline in measured capital input, a leave-one-year-out sensitivity analysis was conducted to assess whether the main productivity results were disproportionately influenced by this observation. As shown in Table 4, excluding 2016 reduces the average traditional TFP growth from 4.64% to 2.93% and the average CO₂-adjusted TFP growth from 5.04% to 3.36%. This indicates that the unusually high productivity growth recorded in 2016 materially affects the average productivity estimates over the sample period.

However, the average CO₂-based adjustment remains positive and changes only slightly, from 0.394 to 0.430 percentage points, when 2016 is excluded. Moreover, the CO₂-based adjustment in 2016 itself is relatively small (+0.12 percentage points), compared with the substantially larger adjustment observed in 2020 (+2.65 percentage points). These results suggest that the exceptional 2016 observation is important for the magnitude of average measured TFP growth, but it does not appear to be the primary source of the CO₂-based adjustment identified in the analysis.

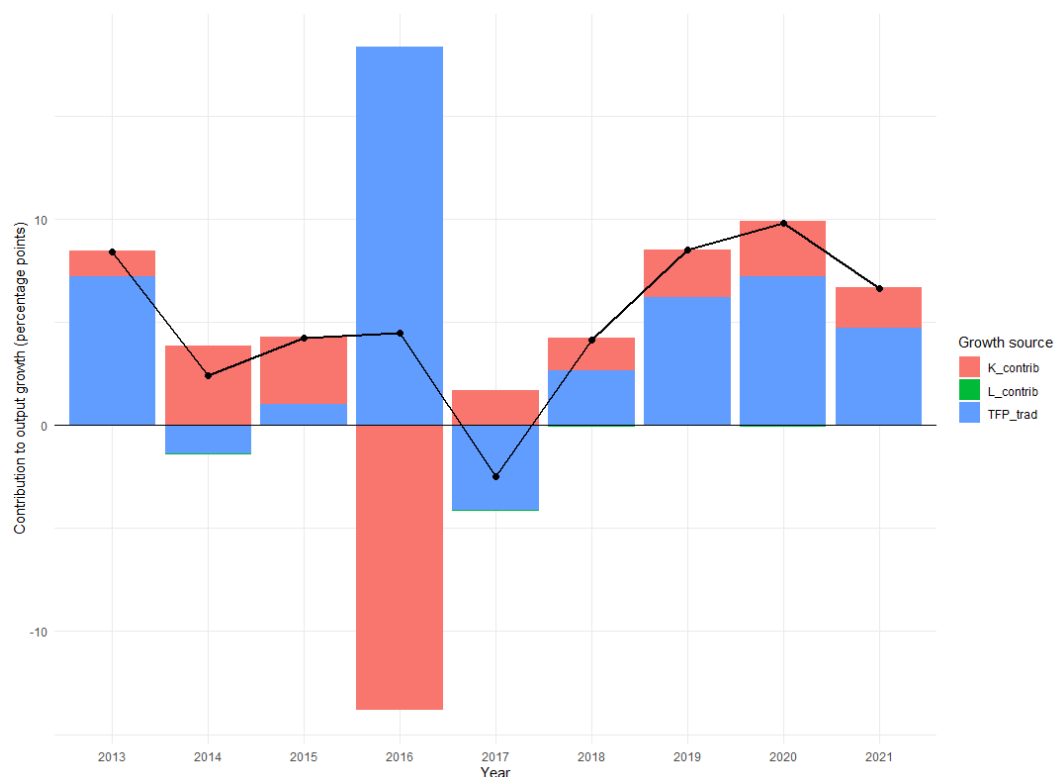
Table 4. Sensitivity of Productivity Growth to the 2016 Capital-Input Observation

Specification	Traditional TFP (%)	CO ₂ -Adjusted TFP (%)	Environmental Adjustment (pp)
Full sample	4.64	5.04	0.394
Excluding 2016	2.93	3.36	0.430
Difference	−1.71	−1.68	0.04

4.2 Sources of Agricultural Output Growth

Figure 4 shows substantial variation in the sources of agricultural output growth over time. Capital and traditional TFP contributions were both positive in several years, whereas 2016 represents an exceptional case in which a large negative capital contribution coincided with unusually high residual TFP growth. From 2018 onward, positive capital and TFP contributions jointly supported output growth.

Figure 4. Annual Decomposition of Agricultural Output Growth, 2013–2021



Note: Agricultural output growth is decomposed into capital, labor, and traditional TFP contributions. The black line represents actual agricultural output growth. Contributions are measured in percentage points.

4.3 Evolution of Factor Shares

Table 5 reports the factor shares used in the growth-accounting decomposition. The labor factor share remained small throughout the sample period, whereas the capital factor shares accounted for most of the total factor share. The AGDP-weighted labor share was relatively stable between 2013 and 2017, ranging from 0.014 to 0.015, but declined thereafter to 0.006 in 2020 before remaining at approximately 0.006 in 2021. Correspondingly, the capital factor share increased from 0.986 in 2017 to 0.993 in 2020 and 0.994 in 2021. This pattern indicates that changes in the measured capital input receive substantially greater weight than changes in labor input in the growth-accounting decomposition.

The factor shares sum to unity in all years for which lagged observations are available, and the accounting error is 0.000. This diagnostic confirms the arithmetic identity imposed by the CRS assumption, but it does not validate the economic measurement of factor shares.

Table 5. Factor Share Dynamics and Consistency Diagnostics, 2012–2021

Year	Labor Income Share (LIS)	Labor Factor Share (α_L)	Capital Factor Share (α_K)	Factor Share (Sum)
2013	0.014	0.015	0.985	1
2014	0.014	0.014	0.986	1
2015	0.014	0.014	0.986	1
2016	0.014	0.014	0.986	1
2017	0.015	0.015	0.986	1
2018	0.011	0.013	0.987	1
2019	0.008	0.009	0.991	1
2020	0.006	0.007	0.993	1
2021	0.006		0.994	1

4.4 Period-Level Growth Accounting

Table 6 summarizes the growth-accounting decomposition across the three periods. During Period 1 (2013–2014), output growth averaged 5.39%, with capital and traditional TFP contributing 2.54 and 2.90 percentage points, respectively, while the labor contribution was slightly negative (−0.05 percentage points). During Period 2 (2015–2017), average output growth declined to 2.07%, accompanied by negative contributions from both capital (−2.95 percentage points) and labor (−0.06 percentage points). In contrast, traditional TFP growth remained positive at 5.08%, offsetting the negative measured input contributions. This result should be interpreted cautiously because the period includes a substantial decline in measured capital input in 2016, which mechanically increases the residual TFP measure. During Period 3 (2018–2021), output growth increased to 7.28%, accompanied by a positive capital contribution of 2.15 percentage points and continued TFP growth of 5.19%. Overall, the decomposition shows that the relative contributions of capital accumulation and residual productivity varied substantially across the sample periods.

Table 6. Stage-Level Growth Accounting Decomposition

Stage	Period	Output Growth	Capital Contribution	Labor Contribution	TFP Growth
Periods 1	2013–2014	5.39	2.54	-0.05	2.90
Periods 2	2015–2017	2.07	-2.95	-0.06	5.08
Periods 3	2018–2021	7.28	2.15	-0.07	5.19

Notes: Output growth is decomposed into capital contribution, labor contribution, and traditional total factor productivity (TFP) growth. The decomposition satisfies $g_Y = K\text{-contribution} + L\text{-contribution} + TFP_{trad}$. Contributions are reported in percentage points (pp), while output growth and TFP growth are reported as annual percentage changes averaged over each stage.

4.5 CO₂-Based Adjustment in Agricultural TFP Growth

Table 7 compares traditional and CO₂-adjusted TFP growth across the three periods. In Period 1 (2013–2014), CO₂-adjusted TFP growth was 2.609%, compared with 2.897% for traditional TFP, corresponding to a CO₂-based adjustment of −0.289 percentage points. In Period 2 (2015–2017), CO₂-adjusted TFP growth increased slightly above traditional TFP, reaching 5.172% compared with 5.076%, with an adjustment of 0.097 percentage points. The difference became larger in Period 3 (2018–2021), when CO₂-adjusted TFP growth reached 6.153%, compared with 5.194% for traditional TFP, implying an adjustment of 0.959 percentage points. Overall, the CO₂-based adjustment changed from negative in the first period to positive in the subsequent periods and became more pronounced in the later period. This pattern indicates that incorporating the CO₂ component alters the measured growth path of agricultural productivity, particularly during the later part of the sample.

Table 7. Traditional and CO₂-Adjusted TFP Growth across Analytical Periods

Stage	Period	Traditional TFP Growth (%)	CO ₂ -Adjusted TFP Growth (%)	Environmental Adjustment (pp)
Periods 1	2013–2014	2.897	2.609	−0.289
Periods 2	2015–2017	5.076	5.172	0.097
Periods 3	2018–2021	5.194	6.153	0.959

Notes: Traditional TFP excludes the CO₂ adjustment, while CO₂-adjusted TFP incorporates it. The adjustment equals CO₂-adjusted TFP minus traditional TFP and is reported in percentage points (pp). Values are average annual growth rates.

4.6 Cumulative Changes in Agricultural Value Added, Inputs, and Productivity

Table 8 summarizes cumulative changes between 2012 and 2021. Agricultural output increased by 58.60%, while capital input increased by 4.97% and labor input declined by 41.70%. CO₂ emissions decreased by 25.30%. Over the same period, traditional TFP increased by 51.90%, while CO₂-adjusted TFP increased by 57.40%. These results indicate that long-run agricultural output growth occurred alongside substantial productivity growth, declining labor input, and lower CO₂ emissions.

Table 8. Cumulative Changes in Agricultural Output, Inputs, CO₂ Emissions, and Productivity, 2012–2021

Indicator	Cumulative Change (%)
Agricultural value added	58.60
Capital input	4.97
Labor input	–41.70
CO ₂ emissions	–25.30
Traditional TFP	51.90
CO ₂ -adjusted TFP	57.40

Notes: Cumulative changes are calculated by exponentiating the sum of annual log growth rates over 2013–2021. The resulting values represent cumulative changes between 2012 and 2021. Traditional TFP denotes productivity growth calculated without incorporating the CO₂ component, whereas CO₂-adjusted TFP incorporates the CO₂-based environmental adjustment. Values are reported as cumulative percentage changes.

Table 9 decomposes cumulative output log-growth over 2013–2021. The cumulative log-growth of output was 46.10 percentage points, of which 4.83 percentage points came from capital, –0.54 percentage points from labor, and 41.80 percentage points from the traditional TFP residual. The components sum to the cumulative output log-growth, with a negligible decomposition error. The large TFP residual should not be interpreted directly as technological innovation because it may also reflect measurement changes and other factors captured by the residual.

The cumulative CO₂ contribution was –3.55 percentage points. This indicates that changes in CO₂ emissions made a negative contribution to cumulative output growth within the growth-accounting decomposition. As emphasized above, this environmental component represents an accounting contribution rather than a causal effect of emission reductions on productivity.

Table 9. Cumulative Decomposition of Agricultural Output Growth, 2013–2021

Component	Cumulative Log-Growth Contribution (pp)
Agricultural value-added growth	46.1
Capital contribution	4.83
Labor contribution	–0.54
Traditional TFP contribution	41.8
Decomposition error	≈0.00

5. Discussion

5.1 Agricultural Growth, Factor Accumulation, and Productivity Fluctuations

The decomposition indicates substantial variation in the sources of agricultural growth during 2013–2021. Capital contributed positively to several periods, whereas the measured labor contribution remained small and negative. Traditional TFP growth was positive on average but fluctuated considerably over the years. The results therefore do not suggest a simple transition from factor accumulation toward productivity-driven growth.

The unusually high TFP growth in 2016 requires caution. The sharp decline in measured agricultural machinery power generated a large negative capital contribution and, consequently, a large residual TFP estimate. The sensitivity analysis confirms that excluding 2016 substantially reduces average TFP growth. This result highlights the importance of input measurement when interpreting residual productivity growth. The 2016 estimate should therefore not be regarded as direct evidence of an equivalent improvement in underlying agricultural technology.

5.2 Environmental Adjustment and Green Productivity

The CO₂ adjustment changes the measured productivity path most clearly in the later part of the sample. It was slightly negative in the early years but became positive thereafter, with the largest difference occurring in 2020. This pattern coincided with a substantial decline in agricultural CO₂ emissions relative to agricultural output.

The 2020 result illustrates the measurement implications of incorporating environmental performance into growth accounting. The decline in CO₂ intensity increased CO₂-adjusted TFP relative to conventional TFP. However, this adjustment should not be interpreted as a causal productivity effect. The accounting framework does not identify whether changes in emissions

resulted from technological change, input substitution, production restructuring, policy interventions, or other factors. It captures how changes in environmental intensity alter the measured productivity residually.

5.3 Interpreting Exceptional Years and Sensitivity Analysis

The 2016 and 2020 results reflect different sources of variation in the estimates. The 2016 observation is primarily associated with the sensitivity of residual TFP to the measurement of capital input, whereas the 2020 difference between conventional and CO₂-adjusted TFP is associated with the substantial reduction in CO₂ emissions relative to output.

Excluding 2016 reduces average TFP growth substantially, while the average CO₂-based adjustment changes only slightly. The alternative factor-share specification also produces similar average estimates. These results indicate that the 2016 observation affects the magnitude of measured productivity growth but does not account for the broader difference between conventional and CO₂-adjusted productivity.

6. Conclusion

This study examined agricultural productivity growth in China during 2013–2021 using a growth-accounting framework incorporating agricultural CO₂ intensity. The results show considerable year-to-year variation in productivity growth, while traditional TFP remained positive on average across the analytical periods. Capital contributed positively in several periods, whereas the measured labor contribution remained small and negative.

The CO₂-adjusted measure provides an additional perspective on agricultural productivity. The environmental adjustment became more important toward the end of the sample, particularly in 2020 when CO₂ emissions declined substantially relative to agricultural output. At the same time, the sensitivity analysis shows that the unusually high 2016 productivity estimate is closely related to changes in the measured capital input.

Several limitations should be noted. Agricultural machinery power is used as a capital proxy, factor shares rely partly on residual construction, and the environmental adjustment considers CO₂ rather than the full range of agricultural greenhouse gases. In addition, the national aggregate analysis does not capture regional or production-level heterogeneity.

Overall, the findings show that conventional and CO₂-adjusted productivity measures can differ when environmental performance changes substantially relative to agricultural output. Incorporating environmental information into growth accounting therefore provides an additional measurement perspective for assessing agricultural productivity alongside environmental performance.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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