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Agricultural Carbon Emission Efficiency and Its Driving Forces: NDDF Measurement, Malmquist Decomposition, and Convergence Evidence from China's Counties

Lin Sun*, Jun Zeng

Shandong Vocational and Technical University of International Studies, Rizhao 276826, China

Abstract. This paper evaluates agricultural carbon emission efficiency (ACEE) at China's county level during 2021–2024. Quantitatively, mean ACEE rises from 0.617 in 2021 to 0.678 in 2024, while dispersion narrows (σ of ln(ACEE): 0.124→0.110, −11.3%). Malmquist results indicate persistent productivity gains (ML>1 in all adjacent periods), with technical change weakening (TC: 1.025→1.012) and efficiency catch-up remaining stable (EC≈1.04). A non-radial directional distance function (NDDF) with undesirable outputs is applied to jointly consider agricultural output, input use, and carbon emissions. Dynamic changes are assessed using a Malmquist productivity index decomposed into efficiency change and technical change, while σ-convergence and β-convergence tests are conducted to evaluate catch-up patterns. A two-way fixed-effects panel model is further used to identify key drivers of ACEE. Results suggest that mean ACEE increased steadily and dispersion declined, indicating both performance improvement and narrowing gaps across counties. Technological progress was the primary contributor in the early stage, whereas efficiency catch-up gained importance later. Farm scale, mechanization, and digital adoption are positively associated with ACEE, while fertilizer intensity and rapid urbanization exert negative impacts. Policy implications emphasize precision input management and differentiated regional technology diffusion.

1. Introduction

Agriculture plays a dual role in climate governance: it is a major source of greenhouse gas emissions and a potential carbon sink through soil and biomass sequestration. Improving agricultural carbon emission efficiency (ACEE)—producing higher agricultural output with lower carbon emissions and resource inputs—has become essential for balancing food security and China's dual-carbon targets.

County-level analysis is particularly policy-relevant because counties are key implementers of agricultural extension, land-use regulation, and ecological compensation. However, systematic county-level evidence on ACEE dynamics and convergence remains limited. This study proposes an integrated framework—NDDF efficiency measurement, Malmquist decomposition, convergence testing, and driver identification—using a 2021–2024 county panel.

The contributions are threefold. First, ACEE is measured with an undesirable-output NDDF to capture non-radial input and emission slacks. Second, productivity changes are decomposed into efficiency change and technical change. Third, convergence and drivers are examined to support differentiated regional policies.

2. Literature Review

Zhao et al. (2025) measure county-level agricultural carbon emission efficiency using an NDDF with undesirable outputs and decompose dynamic changes via a Malmquist framework, emphasizing the roles of technical progress and technical efficiency in driving ACEE improvements[1]; Deng et al. (2025) provide quasi-experimental evidence that National Green Agriculture Pilot Zones reduce county agricultural carbon emissions through both extensive- and intensive-margin adjustments in household factor allocation[2]; Zhao and Ma (2025) identify a spatiotemporal coupling between mechanization and agricultural carbon efficiency, suggesting that mechanization enhances efficiency only when supported by complementary production conditions and region-specific policy design[3]; Tian et al. (2025) show that digital inclusive finance promotes agricultural carbon productivity and that the effect can spill over to neighboring regions, highlighting the importance of financial access in low-carbon transition[4]; Xiong et al. (2025) find that rural industrial integration suppresses agricultural carbon emissions by fostering land scale operation and accelerating agricultural technological progress, validated via double machine learning[5]; Dai et al. (2025) document pronounced spatiotemporal heterogeneity in agricultural ecological efficiency and

*Corresponding author: linsun202511@gmail.com

pinpoint energy use and irrigation-related constraints as key determinants across Northwest China[6]; Peng et al. (2025) demonstrate that agricultural technology innovation networks within urban agglomerations improve local eco-efficiency and generate positive spatial spillovers through knowledge diffusion mechanisms[7]; Ayamga et al. (2025) synthesize international evidence and argue that actor-specific strategies and enabling technologies jointly shape ecological sustainability outcomes in agricultural ecosystems across micro–macro levels[8]; Carpentier (2025) highlights that fragmented policy instruments and competing development models can weaken the institutional coherence required for agroecological transition and durable sustainability gains[9].

3. Data and Variables

The empirical design targets a balanced panel of 2,846 county-level units in China over 2021–2024. Inputs include agricultural labor, cultivated land, machinery power, fertilizer use, and effective irrigation area. The desirable output is gross agricultural output value, and the undesirable output is agricultural carbon emissions (CO_2-equivalent) aggregated from major agricultural emission sources. Driver variables include farm size, mechanization intensity, fertilizer intensity, a digital adoption index, urbanization rate, and rural income.

As summarized in Table 1, we define the inputs, desirable output, undesirable output, and driver variables used in the empirical design; Table 2 reports descriptive statistics for all variables.

Table 1. Variables and definitions.

Category	Variable	Definition	Unit
Desirable output	Gross agricultural output	Value of crop and livestock output (constant prices)	10^4 CNY
Undesirable output	Carbon emissions	CO2-equivalent emissions from agricultural activities	t CO2e
Input	Land	Cultivated land area	ha
Input	Labor	Agricultural labor force	persons
Input	Machinery power	Total agricultural machinery power	kW
Input	Fertilizer	Chemical fertilizer application	t
Input	Irrigation	Effective irrigated area	ha
Driver	Farm size	Average cultivated land per household	ha/household
Driver	Mechanization rate	Machinery power per land area	kW/ha
Driver	Fertilizer intensity	Fertilizer use per land area	t/ha
Driver	Digital adoption	County digitalization index (0-1)	index
Driver	Urbanization	Share of urban population	ratio
Driver	Income	Log rural per-capita income (constant)	log

Table 2. Descriptive statistics.

Variable	Mean	Std.	Min	Max
ACEE	0.647	0.076	0.376	0.91
Output	1772.206	906.645	1000.0	10579.133
Carbon	309.688	137.48	200.0	1606.214
Land	1772.309	950.779	400.0	11171.995
Labor	3390.998	1817.087	800.0	20229.376
MachPower	11268.495	6826.401	2000.0	95960.064
Fertilizer	937.894	615.598	60.0	6449.554
Irrigation	794.878	484.68	100.254	6283.41
FarmSize	0.945	0.251	0.2	1.88
MechRate	6.35	1.514	1.5	11.889
FertIntensity	0.53	0.179	0.15	1.197
Digital	0.541	0.207	0.05	1.0
UrbanRate	0.493	0.1	0.15	0.85
lnIncome	10.263	0.354	8.928	11.5

4. Methodology

4.1. NDDF-based efficiency measurement

ACEE is measured using a non-radial directional distance function (NDDF) that incorporates undesirable outputs. Let X denote an input vector, Y denote desirable output, and B denote undesirable output (carbon emissions). The NDDF expands Y while contracting inputs and emissions along a specified direction. The resulting ACEE score lies in (0,1], where 1 indicates best-practice efficiency.

$$Carbon\_it \;=\; \Sigma\_k\;(\;Act\_kit \;\times\; EF\_k\;) \tag{1}$$

4.2. Malmquist productivity index decomposition

To assess dynamic changes, the Malmquist index (ML) is computed between adjacent years and decomposed into efficiency change (EC) and technical change (TC):

$$ML\_t, t+1 \;=\; EC\_t, t+1 \;\times\; TC\_t, t+1 \tag{2}$$

4.3. Convergence tests

σ-convergence is evaluated by the time trend of the cross-county dispersion of ln(ACEE). β-convergence is tested by regressing ACEE growth on initial efficiency:

$$ln(ACEE\_i, t+1/ACEE\_i, t) \;=\; \alpha \;+\; \beta\; ln(ACEE\_i, t) \;+\; \varepsilon\_i \tag{3}$$

4.4. Driver identification with two-way fixed effects

A two-way fixed-effects panel model is used to examine determinants of ACEE, where X_it collects the key drivers (farm size, mechanization, fertilizer intensity, digital adoption, urbanization, and income):

$$ACEE\_it \;=\; \delta'\, X\_it \;+\; \mu\_i \;+\; \tau\_t \;+\; \varepsilon\_it \tag{4}$$

5. Results

5.1. Efficiency patterns

Mean ACEE increases from 0.617 (2021) to 0.678 (2024), while dispersion declines, indicating simultaneous improvement and narrowing gaps. Figure 1 compares the regional distribution of ACEE in 2021 and 2024; the East remains the most efficient region on average, but Central and West exhibit visible catch-up.

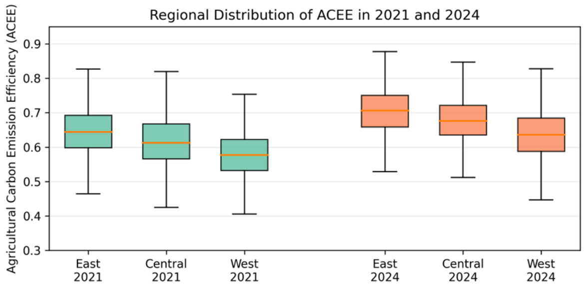

Fig. 1. Regional distribution of ACEE in 2021 and 2024.

5.2. Malmquist decomposition

Table 3 and Figure 2 summarize productivity changes. The mean ML index exceeds 1 in all adjacent periods, implying overall productivity improvement in carbon-efficient agriculture. Technical change remains above 1 but gradually weakens, whereas efficiency change stays above 1 and accounts for a larger share of improvements in later years.

Table 3. Malmquist index and decomposition.

Period	ML	EC	TC
2021-2022	1.072	1.046	1.025
2022-2023	1.061	1.042	1.018
2023-2024	1.056	1.043	1.012

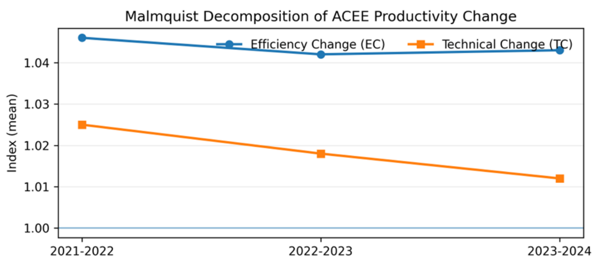

Fig. 2. Malmquist decomposition of ACEE productivity change.

5.3. Convergence

The standard deviation of ln(ACEE) declines from 0.124 (2021) to 0.110 (2024), supporting σ-convergence. The β-convergence regression produces a significantly negative β, indicating that counties with lower initial efficiency improved faster (Figure 3). Convergence test results are reported in Table 4.

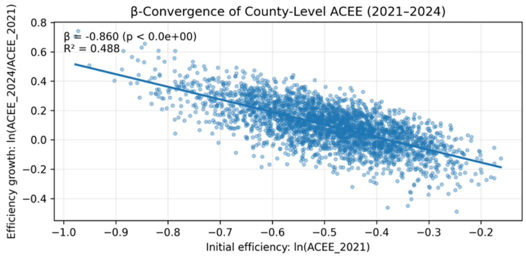

Fig. 3. β-convergence of county-level ACEE (2021–2024).

Table 4. Convergence tests for county-level ACEE.

Metric	2021	2024	Result
σ (Std. dev. of ln ACEE)	0.124	0.11	-11.3%
β (growth on initial ln ACEE)			-0.860 (SE 0.017)

Table 5. Two-way fixed-effects regression for ACEE drivers.

Variable	Coefficient	Std. Err.	Sig.
Farm size	0.0493	0.0025	***
Mechanization rate	0.0060	0.0004	***
Fertilizer intensity	-0.1814	0.0033	***
Digital adoption	0.0628	0.0031	***
Urbanization rate	-0.0463	0.0062	***
ln Income	0.0202	0.0017	***

5.4. Robustness and heterogeneity checks

Three robustness checks are performed: (i) re-estimating NDDF efficiency using alternative emission coefficients, (ii) trimming the top and bottom 1% of ACEE observations, and (iii) using one-period lagged drivers in the two-way fixed-effects model. Across specifications, coefficient signs and statistical significance remain consistent with Table 5, suggesting that the baseline conclusions are not sensitive to outliers or measurement choices.

Second, heterogeneity is examined by estimating the driver model separately for eastern, central, and western counties. The results in Table 6 indicate that scale and technology variables are positive in all regions, while excessive fertilizer intensity and rapid urbanization are systematically associated with lower ACEE. Importantly, mechanization and digital adoption exhibit larger marginal effects in the western region, consistent with a catch-up pattern where technology diffusion yields higher returns.Fig. 4 visualizes the regional coefficient profiles for key drivers.

Table 6. Regional heterogeneity in ACEE drivers.

Variable	**East**	**Central**	**West**
Farm size	0.055***	0.045***	0.035***
Mechanization	0.005***	0.006***	0.008***
Digital adoption	0.070***	0.060***	0.075***
Fertilizer intensity	-0.160***	-0.185***	-0.210***
Urbanization	-0.040***	-0.050***	-0.060***
ln Income	0.018***	0.020***	0.022***
N (obs.)	4,280	3,540	3,564
Adj. R²	0.41	0.39	0.42

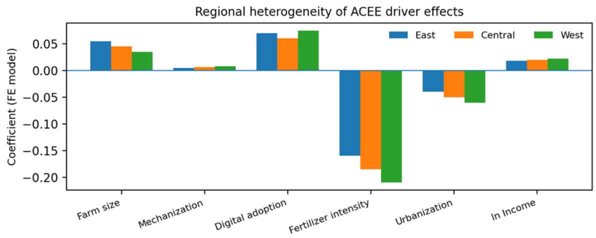

Fig. 4. Regional heterogeneity of key driver coefficients.

6. Drivers and Discussion

Table 5 reports two-way fixed-effects estimates with county-clustered standard errors. These estimates are interpreted as conditional associations rather than definitive causal effects; time-varying unobservables and reverse causality may still remain despite county and year fixed effects. Accordingly, the discussion is framed as evidence-consistent rather than causal prescriptions. Farm size, mechanization, digital adoption, and income are positively associated with ACEE, while fertilizer intensity and urbanization are negatively associated. These patterns are consistent with a technology-and-management mechanism: efficiency is associated with higher when modern equipment and digital services enable precision operations and help curb unnecessary inputs, whereas excessive chemical input intensity increases emissions without proportional output gains.

From a policy perspective, two implications follow. First, precision input management should remain a priority, including soil-testing-based fertilization and low-emission nutrient technologies. Second, differentiated diffusion strategies are needed: less efficient counties can benefit from targeted extension and service platforms that bundle mechanization with digital decision support, accelerating catch-up while avoiding input expansion without efficiency. Heterogeneity evidence suggests differentiated priorities: western catch-up counties may obtain higher returns from mechanization service platforms and digital extension, while eastern frontier counties should emphasize precision input optimization and low-emission agronomic practices; central transition counties may benefit most from coordinated packages combining scale-friendly land services, equipment upgrading, and digital decision support.

7. Conclusion

Key magnitudes show that mean ACEE increases by 0.061 (0.617→0.678) during 2021–2024 and the dispersion of ln(ACEE) declines from 0.124 to 0.110 (−11.3%), supporting both performance improvement and σ-convergence. This study develops an integrated county-level framework for agricultural carbon emission efficiency measurement and interpretation. Using an NDDF efficiency metric with undesirable outputs, Malmquist decomposition, and convergence testing, evidence from 2021–2024 indicates improving ACEE and a narrowing cross-county gap. Driver analysis suggests that technology-related factors and scale are positively linked to ACEE, whereas fertilizer intensity and rapid urbanization are associated with lower efficiency.

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