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Farm size and greenhouse gas emission: Do large farms in China produce more emissions?

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Abstract: Farms are key to agricultural advancement and carbon emission reduction. Understanding the influence of farm size on emissions is vital for eco-friendly farming. Our study used an econometric model with instrumental variable adjustments to examine the effect of farm size on greenhouse gas emissions, revealing an inverted U-shaped relationship. The findings revealed that emissions increased with farm size until a peak and then decreased. We identified an optimal farm size range (0.45 km² to 0.58 km²) for lower emissions, where the farm size maintaining the lowest greenhouse gas emissions per unit area was 0.58 km², while the lowest greenhouse gas (GHG) emissions per capita occured at a farm size of 0.69 km². Reducing emissions intensity per unit area is easier than reducing GHG emissions per person. Policymakers should prioritise promoting the expansion to moderately sized farms as a means of achieving emission reduction targets rather than solely increasing the number of farms. Overall, these insights offer policymakers novel approaches for ecological farm planning and the transition toward a low-carbon agriculture sector.

Keywords: econometric model; agricultural area; greenhouse emission; optimum scale

To expedite the progression of ecological farming and catalyse the shift toward sustainable, green, and low-carbon agricultural practices, scholars worldwide have conducted extensive research on greenhouse gas (GHG) emissions, contributory factors, and evaluation methodologies associated with agricultural endeavours (Bekun and Alola 2022; Han et al. 2023). Investigations have revealed several determinants of GHG emissions with agricultural origins, such as land utilisation, management techniques, the prevalent use of pesticides and fertilisers, mechanisation in agriculture, combustion of biomass, livestock enteric fermentation, manure handling, and soil tilling (Garnier et al. 2019). Furthermore, due to stark differences in regional agricultural structures, climatic conditions, levels of management practices, and developmental phases, the GHG emis-

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sions from farms exhibit considerable regional disparities (Adedoyin et al. 2020; Xuan et al. 2023). Regarding the scale of farms, GHG emissions are influenced by factors including management strategies, feed systems, and agricultural policies (Laborde et al. 2021). Mairura et al. (2023) delved into GHG emissions originating from diverse soil fertility management tactics on maise-cultivating farms, finding the lowest GHG emissions with the combined use of fertiliser and manure. Research conducted by Berzina et al. (2019) into the effects of manure management in animal agriculture in Latvia revealed that 73% of the aggregate GHG emissions from animal husbandry stem from the digestive processes of animals, while a mere 27% are attributable to the handling of farm manure.

In examining the impact of farm size on GHG emissions, it is often hypothesised that an increase in farm size leads to higher GHG emissions due to a scale effect. Evidence indicates that the carbon footprint of larger farms, those encompassing more than 20 ha, is smaller than that of their smaller counterparts, which cover less than 0.7 ha (Xu et al. 2022). Other researchers have stated that small, cultivated farms increase the efficiency of GHG emissions (Omotilewa et al. 2021), but discussions on the topic have been mixed. A few studies examining farm size effects on GHG emissions have shown that smaller, denser farms emit twice as much GHG as larger farms (Escribano et al. 2022; Xu et al. 2022). Other studies have revealed the absence of any discernible link between the scale of agricultural enterprises and the volume of GHG emissions they produce (Alemu et al. 2017), mainly due to the diversity of production systems. The above studies investigated the influence of farm size on GHG emissions from manure management and production system perspectives, but none of them specified an appropriate size for minimising GHG emissions per unit area. Therefore, the exploration of farm size's effect on GHG emissions and the determination of an ideal scale remain limited, offering scant insight into national GHG reduction goals and the crafting of adaptive strategies. Furthermore, existing regional studies fail to capture the nationwide spatio-temporal trends of GHG emissions, thus obscuring the impact of national emissions policies.

In this context, our study examined the interplay between farm size and GHG emissions from agricultural sources across China from 2000 to 2022. We aimed to identify an optimal farm size for minimising GHG emissions per unit area, providing critical guidance for fine-tuning China's future agricultural emission reduction strategies and policies.

MATERIAL AND METHODS

Econometric model

The STIRPAT model ($I_i = a_i P_i^b A_i^c T_i^d e_i$) was formulated to unravel the complexity of environmental challenges, featuring a constant term a_i, a random disturbance term e_i, and the parameters of the variables P, A, T (denoted by b, c, and d, respectively), with i indicating a single unit. By incorporating panel data and applying logarithmic transformation to both sides of the equation, we formulated the following linear regression model:

$$\ln I_{it} = \ln a_i + b\ln P_{it} + c\ln A_{it} + d\ln T_{it} + e_{it} \tag{1}$$

where: I – causes of environmental issues; P – population growth; A – affluence; T – unfavourable environmental technology or the impact per unit of economic activity; e_{it} – random disturbance term.

Researchers have expanded this base model by incorporating supplementary explanatory variables as surrogates for T, aiming to explicate the influences of factors other than P and A on I. The dependent variable I often encompasses a proxy variable for the GHG emission index, which is intertwined with ecological wellbeing. In alignment with the study's aims, we constructed a foundational regression model (2) to scrutinise farm GHG emissions:

$$\ln GHG_{it} = \ln a_i + \beta \ln size_{it} + b\ln P_{it} + c\ln A_{it} + \\ + d\ln T_{it} + p_i + q_t + e_{it} \tag{2}$$

where: GHG – greenhouse gas; $size$ – the core explanatory variable of farm size; p – farm individual effect used to capture unobserved individual heterogeneity that affects greenhouse gas emission q – time effect.

Model (2) was designed to pare down the complex interactions among influential factors, thereby promoting individual factor analysis within a decomposition framework. Within the model, i symbolises farm enterprises and t connotes time, while GHG emissions are represented by the variable GHG. Nonetheless, it is essential to recognise the limitations of the IPAT (Impact = Population × Affluence × Technology) framework, which lacks the capacity to extract the effects of solitary factors or to examine hypotheses related to diverse environmental influences. The primary exploratory variable $size$ is farm size, with β serving as the principal parameter. The model also incorporated effects from individual farm impacts, signified by p_i, and temporal effects, denoted by q_t. Farm area was taken

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as the primary determinant of farm size, while controls such as the *per capita* GDP of each province's agricultural areas and other covariates were compacted into ($\vec{X}_{it}$). Hence, model (2) transforms into:

$$\ln GHG_{it} = \alpha_0 + \alpha_1 \ln far_{it} + \rho \vec{X}_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \quad (3)$$

where: far – farm area; ρ – the coefficient of control variable X; μ – farm individual effect used to capture unobserved individual heterogeneity that affects greenhouse gas emission; υ – time effect; ε – random disturbance term.

In model (3), we analysed the effectiveness of common methodologies such as least squares and fixed effects, facilitating the assessment of economic and other variables on GHG emission impacts. Given the complex dynamics of farm size on greenhouse emissions, including management evolution, scientific advancements, and policy shifts, emissions may exhibit non-linear trajectories. We introduced a non-linear variant into our regression model (3) by embedding a quadratic term for farm size:

$$\ln GHG_{it} = \beta_0 + \beta_1 \ln far_{it} + \beta_2 \mathrm{S}\ln Par_{it} + \lambda \vec{Y}_{it} + \mu_i + \eta_t + \sigma_{it} \quad (4)$$

where: λ – coefficient of control variable Y; $\vec{Y}_{it}$ – control variables, including per capita GDP and its quadratic terms, as well as other variables; μ – farm individual effect used to capture unobserved individual heterogeneity that affects greenhouse gas emission; η – time effect; σ – random disturbance term.

Model (4) featured Sln*far* as the quadratic term of ln*far*, with all other variables remaining consistent with model (3). We introduced categorical variables reflecting different farm sizes to address certain model restrictions, utilising small farms as the reference point. These categories and their associated interaction terms were integrated into model (3), culminating in an enriched non-linear model:

$$\ln GHG_{it} = \gamma_0 + \gamma_1 \ln far_{it} + \sum_{k=1}^{4} \theta_k size_{it,k} \ln far_{it} + \vartheta \vec{Z}_{it} + \mu_i + \tau_t + \upsilon_{it} \quad (5)$$

where: ϑ – coefficient of the control variable; $\vec{Z}_{it}$ – control variable, including per capita GDP and its quadratic terms, as well as other variables; μ – farm individual effect used to capture unobserved individual heterogeneity that affects greenhouse gas emission; τ – time effect; υ – a random disturbance term.

In model (5), the terms $size_{it,k}$ and $\ln far_{it}$ represented the interaction of the dummy variable with farm size, where $size_{it,k}$ is the dummy variable considered, and the residual component aligns with model (3).

Variables description and data

GHG emissions. To represent and quantify GHG emissions in China's agricultural sector, GHG emission intensity per unit area and *per capita* were chosen as more effective indicators. The IPCC coefficient methodology was used to calculate GHG emissions. Emissions were obtained by multiplying the activity of the source by the corresponding factor [refer to the Electronic supplementary material (ESM)]. GHG emissions from four sources (nitrous oxide emissions from agricultural land, methane emissions from rice fields, methane emissions from animal enteric fermentation, and methane emissions from animal manure management) were first calculated. GHG emissions per unit area and *per capita* were calculated. A comparative analysis revealed a similar spatial distribution pattern for both metrics across China. Notably, there was a higher emission intensity in the northwestern areas juxtaposed against a lower intensity in the economically prosperous eastern coastal zones (Figure 1). When considering the emission intensity per unit area, it was observed that regions like Shandong, Henan, Hubei, and the municipality of Chongqing have transitioned to lower intensity zones, registering emissions beneath 417.7 Mt CO_2-eq in the benchmark year of 2020. Conversely, Beijing and Tianjin exhibited a rise in their emission intensities. In the context o× in the provinces constituting the North China Plain, whereas an uptick was recorded in the three northeastern provinces and Gansu province.

Farm size. At the beginning of the 21st century, farms in China were scattered across various provinces, with presence in Heilongjiang, Liaoning, Hebei, Shanxi, Hainan, Fujian, et al. This pattern underwent a marked transformation by 2020, witnessing a discernible expansion in the farm area, aggregated in regions characterised by economic robustness, specifically eastwards of the Hu Huanyong Line. Additionally, this agglomeration of agricultural activity extended into northwestern Xinjiang, southern Tibet, and southeastern Inner Mongolia. This study identified farm size as a critical explanatory variable, bifurcated into two distinct categories: physical farm area and number of farm employees. Through the application of regression analysis, the influence of farm size on GHG emissions was scrutinised. To enhance the robustness of the analysis,

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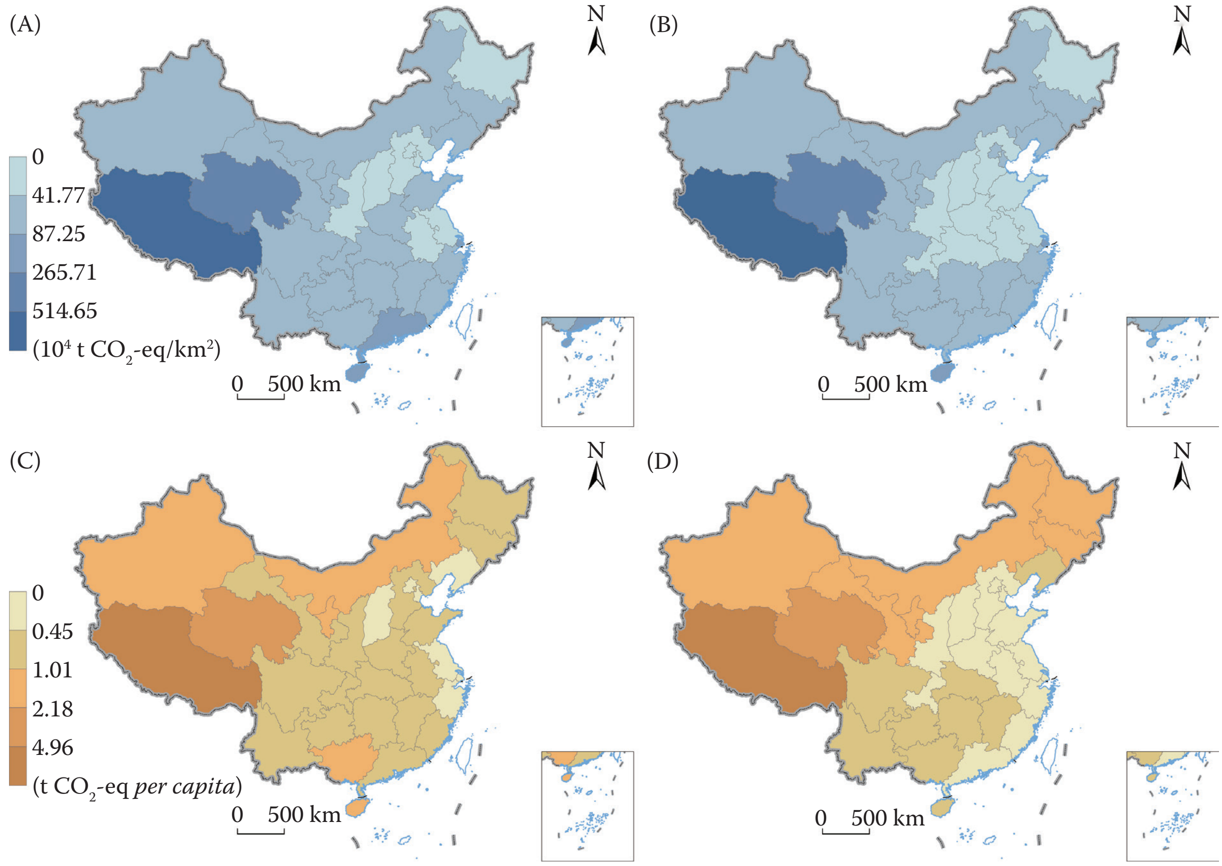

Figure 1. Agricultural green house gas (GHG) emission intensity per unit area (A) 2000, (B) 2020 and *per capita* (C) 2000, (D) 2020

Source: Adapted from Zhang et al. (2023)

the number of farm employees was used as a surrogate indicator for farm population size.

Control variables. To address potential omitted variable bias, this study incorporated several factors influencing farm-related GHG emissions: the economic development level, pesticide and fertiliser use, irrigation, technological advancement, management quality, and agricultural policy impacts. Economic development was gauged by the *per capita* GDP of each agricultural district within provinces, with the square of *per capita* GDP included to test the Environmental Kuznets Curve hypothesis. Pesticides derived from fossil fuel-based raw materials and nitrogen fertilisers, which release nitrous oxide through soil processes, represented significant indirect GHG sources in agriculture, while machinery use represented a direct source.

Technological advancement heralds an upsurge in research and development investment, paving the way for a reduction in GHG emissions. Management quality reflects the extent to which investments are made in intelligent agricultural solutions, including advanced farm lighting, pest control systems, and robotic automation. The national highway system served as a surrogate indicator for transportation services, while the introduction of a policy dummy variable, assigned a value of zero before 2019 and one after, effectively encapsulated the agricultural policy changes aimed at reducing emissions.

China's development of an extensive national highway network centred on capital cities has facilitated agricultural product transport and local socio-economic growth (Figure 2A). Pesticide and fertiliser trends from 2000 to 2020 displayed similar patterns, peaking in 2013–2014 before declining (Figures 2B, 2C). The country's effective irrigated agricultural land generally expanded despite a minor dip in 2013 and a recent slowdown in growth (Figure 2D). A noticeable drop in the total power of agricultural machinery in 2016 reflects the advancement in mechanisation and an upgrade in tractor quality, reducing the number of less efficient, smaller tractors.

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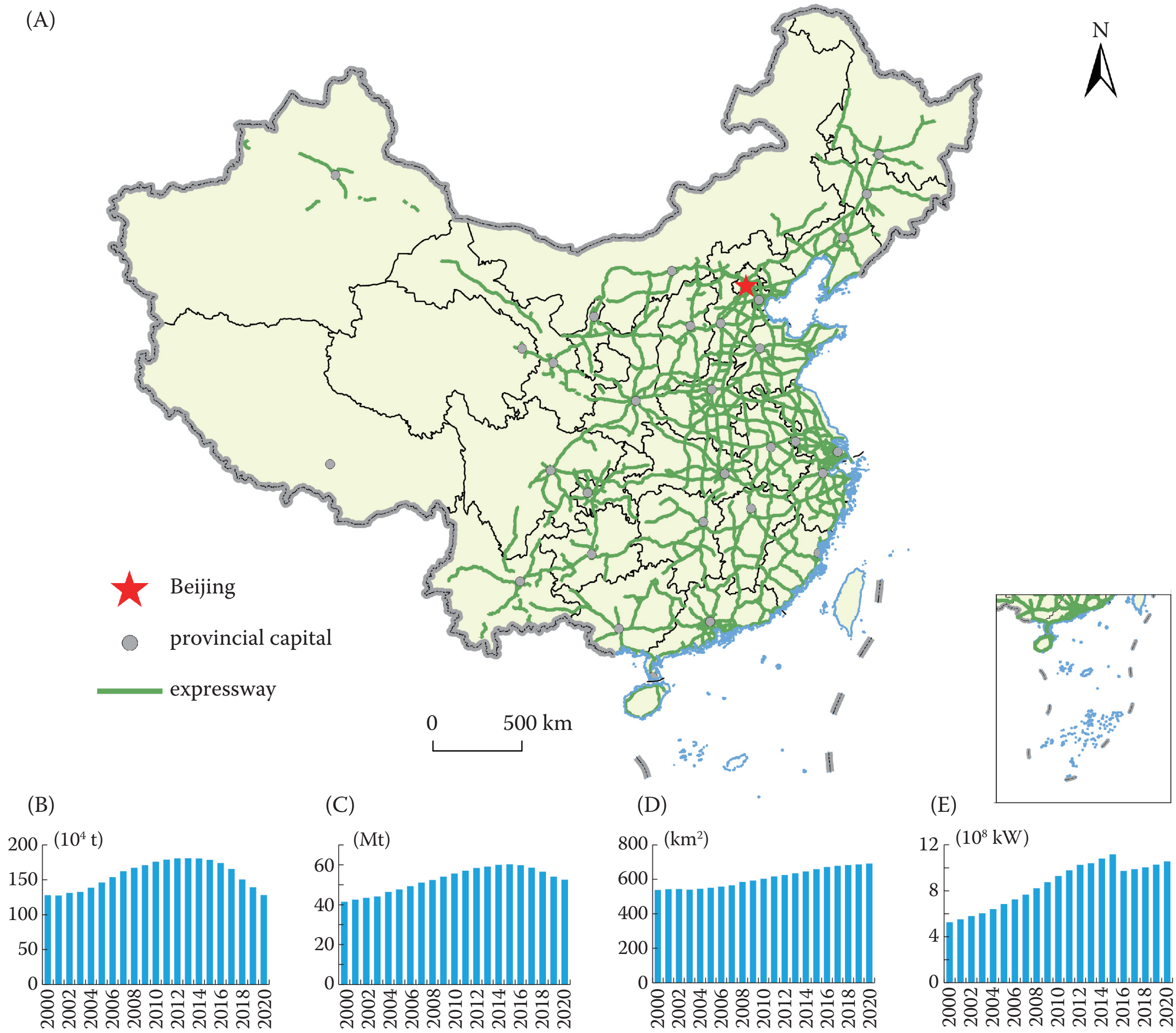

Figure 2. Data description (A) China's expressway map; (B) pesticide use; (C) fertilizer application; (D) effective irrigated area; (E) gross power of agricultural machinery

Source: Data from National Bureau of Statistics (2000–2020): China Statistical Yearbook (China Statistics Press)

Data sources. With an emphasis on the reliability and uniformity of the data, this research assembled a dataset of Chinese agricultural enterprises spanning 2000 to 2020, including 6.031 million farms in the analysis, including 3.8 million family farms, 2.216 million legally registered farmer cooperatives, and 15 000 organised cooperatives. There were 1.765 million grain-growing family farms and 542 000 grain-growing cooperatives. There were 3.217 million family farms and 1.942 million cooperatives engaged in breeding, respectively. The dataset incorporated farm size and geospatial information gleaned from thorough enterprise surveys. The emissions of carbon dioxide, methane, and nitrous oxide from these enterprises were used to calculate GHG emissions using the coefficient methodology prescribed by the Intergovernmental Panel on Climate Change. The acquired data encompassed variables such as pesticide and fertiliser usage, irrigation methods, technological advancement, management efficacy, and agricultural policy reforms, all of which were sourced from the National Bureau of Statistics (2000–2020): China Statistical Yearbook, Ministry of Agriculture and Rural Affairs (2000–2020): China Agricuture Yearbook, National Bureau of Statistics. (2000–2020): China Rural Statistical Yearbook, Ministry of Ecology and Environment (2000–2020):

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Table 1. Descriptive statistics, 2000–2020

Variable	Definition	Unit	Mean	SD	Minimum	Maximum
gei	GHG emissions intensity	10 000 t CO_2eq/km^2	107.6300	223.0500	20.1100	1 519.2400
pge	*per capita* agricultural GHG emissions	t CO_2eq/people	0.6500	0.0430	0.5300	0.7230
far	farm area	km^2	0.0142	0.0902	0.0002	17.613
pfa	population of farm	10 000 people	0.0012	0.0040	0.0000	0.0200
edev	economic development level	USD 1 369/person	3.4300	2.1020	0.7940	7.1800
pes	pesticide	10 000 t	156.6400	19.8700	127.4800	180.7700
fer	fertiliser	million tonnes	5 258.0700	610.9400	4 146.4100	6 022.6000
irri	irrigation	km^2	607.3400	54.8600	538.2000	691.6100
agm	agricultural machinery	10 000 kW	85 658.7000	19 121.2100	52 573.6100	111 728.0700
mle	management level	%	0.4700	0.1700	0.2600	0.8200
apol	agricultural policy	0 or 1	0.5700	0.4800	0.0000	1.0000
rail	whether there was a rail passing through	0 or 1	0.6700	0.5300	0.0000	1.0000

gei – GHG intensity per ha, encapsulating the emissions produced per km^2 of farm area; *pge* – *per capita* GHG emission intensity, reflecting the emissions attributed to each individual; *edev* – economic development level of each agricultural province, calibrated according to the *per capita* GDP; a *per capita* GDP of USD 1 369 is denominated as a value of 1, and subsequent values are adjusted in line with the actual GDP; *pes* – pesticide usage amount, noted in 10 000-tonne units; *fer* – quantity of fertilizers employed, expressed in millions of tons; *irri* – span of irrigated agricultural land, measured in km^2; *agm* – input of agricultural machinery, delineated in kilowatts; *mle* – diverse management levels across farms, a value of 0 indicates an absence of any management strategies; *apol* – agricultural policy, with its value indicating the presence (1) or lack (0) of agricultural policy in the area; *rail* – existence of railway infrastructure near the farm; the presence of a railway is marked as 1, while its absence is 0; GHG – greenhouse gas

Source: Adapted from Adedoyin et al. (2020)

China Environmental Yearbook, miscellaneous regional statistical yearbooks, and a diverse array of bulletins. Gaps in the data were filled by employing pertinent econometric methods and drawing from the statistical yearbooks of the corresponding provinces to ensure a comprehensive dataset. The outcomes for each pivotal variable are tabulated in Table 1.

Endogeneity discussion. Farm size may interact with GHG emissions to a certain degree. However, absolute independence and exogeneity are not always assured. This interplay could generate reverse causality when assessing the impact of farm size growth on GHG emissions, potentially biasing parameter estimates. Therefore, incorporating instrumental variables into the econometric model is essential to effectively address possible endogeneity issues.

To preserve the model's exogeneity, instrumental variables that were strongly related to endogenous variables were selected. In our analysis, the existence of a highway through a farm as of 2020 served as the instrumental variable for farm size. This choice was informed by two main considerations. First, highways are vital in boosting commodity flow and economic expansion, fostering local population concentration, and aiding in the formation of modern farms, thereby demonstrating a strong link with farm size expansion. Second, highway development and placement are influenced by technological, social, and economic conditions at the time. By treating highway presence as a natural experiment, we ensured the exogeneity of the instrumental variables and minimised its direct effect on current on-farm GHG emissions.

RESULTS

Regression model and analysis

Linear analytical model and analysis. This study explored the linear relationship between escalating farm size and GHG emissions by utilising a regression model (2). GHG emissions were quantified as GHG emission intensity (*gei*) and *per capita* GHG emissions (*pge*), acting as dependent variables. Farm size was represented by explanatory variables such as farm area, GDP *per capita*, and the quadratic term of the GDP per capita, all relating to agricultural districts within each province. A thorough set of control

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Table 2. Estimation of linear model

Variable	(1) OLS-*gei*	(2) FE-*gei*	(3) OLS-*pge*	(4) FE-*pge*
ln*far*	0.1381 (3.7628)***	0.1357 (5.4890)***	0.0682 (1.9978)**	0.0473 (4.3213)***
ln*edev*	0.1789 (2.0345)**	0.1631 (1.1865)*	0.1832 (2.2541)**	0.1951 (0.8382)*
Sln*edev*	−0.1567 (−2.2376)**	−0.1478 (−2.6425)*	−0.1637 (−2.4678)**	−0.1842 (−2.4932)**
ln*pes*	0.1387* (6.2353)***	0.1389** (4.3287)***	0.1825* (3.8765)***	0.1374** (6.9271)***
ln*fer*	0.1825 (4.2329)***	0.1526** (6.8923)***	0.1151*** (1.9832)**	0.1774** (3.0483)***
ln*irri*	−0.0823 (−1.7256)*	−0.0926 (−0.6374)	−0.0792 (0.7951)	−0.0792 (−0.6743)
ln*agm*	−0.1271 (−1.9826)**	−0.1434 (−2.0328)**	−0.1205 (−3.2018)***	−0.1522 (−2.7533)***
ln*mle*	−0.0926 (−2.2983)**	−0.0844* (−2.3634)**	−0.0927** (−3.1234)***	−0.0735* (−3.6401)***
apol	−0.1915 (−2.7298)***	−0.2416 (−3.2345)***	−0.1064 (−1.9342)*	−0.2512 (−2.1567)**
_cons	3.8231 (9.2817)***	3.9712 (9.2817)***	3.1824 (9.2817)***	4.9212 (9.2817)***
R^2	0.9153	0.9464	0.8326	0.8859
F-test	–	123.69	–	120.23
Hausman test	–	78.95	–	89.49

*, **, *** significant at 10%, 5%, and 1% level, respectively; the significance levels are denoted using *T* statistics, presented in parentheses; *gei* – GHG intensity per ha, encapsulating the emissions produced per km^2 of farm area; *pge* – *per capita* GHG emission intensity, *far* – farm area; *edev* – economic development level; Sln*edev* – quadratic term of ln*edev*; *pes* – pesticide; *fer* – fertiliser; *irri* – irrigation; *agm* – agricultural machinery; *mle* – management level; *apol* – agricutural policy; *_cons* – constant term
Source: Adapted from Adedoyin et al. (2020)

variables was integrated($\vec{X}_{it}$). Reformulating model (2) as $\ln energy_{it} = \alpha_0 + \alpha_1 \ln psi_{it} + \rho \vec{X}_{it} + \mu_i + \upsilon_t + \varepsilon_{it}$, we adopted model (3) to carry out ordinary least squares (OLS) and fixed effects (EF) estimations for GHG emission intensity and *per capita* GHG emissions as separate dependent variables. The choice to use the individual fixed effects model in this research was substantiated by the results from the *F*-test and the Hausman test, both outlined in Table 2.

In Table 2, the second column demonstrates the estimated results for farm size (measured by farm area), revealing a positive coefficient that insinuates a discernible intensification of GHG emission intensity parallel with farm size increment. In parallel, column 4 indicates a significantly positive coefficient for farm size, signifying that expanding the farm size was associated with an increase in *per capita* GHG emissions. The positive coefficient for economic development (*edev*) detailed in Table 2, contrasted with its negative quadratic term, lent credence to the classical Environmental Kuznets Curve (EKC) hypothesis in the context of economic advancement and farm GHG emissions. This suggests an initial rise followed by a subsequent decline in GHG emissions with ascending economic levels in agricultural zones.

Additional regression results for control variables illuminated the positive influence of pesticides and fertilisers on GHG emission levels, highlighting the addition of GHG through aerosol pesticide particles and vapours. The primary impact of chemical fertilisers on the atmosphere originates from nitrogen-based compounds, where emissions such as nitrous oxide and methane arise from ammonia volatilisation and nitrification-denitrification processes. Although the coefficient for irrigation level was negative for both GHG emission intensity and *per capita* emissions, its impact was not significant, suggesting a minor role in GHG reduction. Enhanced irrigation modified soil water composition, which substantially influenced agricultural GHG emissions. Agricultural mechanisation, indicative of on-farm science and technology applications, exerted a considerable negative effect on both GHG emission metrics, proposing that agricultural mechanisation aided in the abatement of GHG emissions. Implementing advanced agricultural machinery and fostering farm management through AI and IoT technologies stood as viable measures for GHG reduction. Additionally, the regression outcomes portrayed a negative coefficient for agricultural management level on emissions, asserting that elevated management practices curtailed GHG outputs. Lastly, agricultural policy factors exhibited a pronounced negative coefficient, denoting a constraining influence on GHG emissions, whereby policy enforcement augmented farm management efficiency and curbed high-emission activities.

Non-linear analytical model and analysis. Building on the previous theoretical foundation that delineated the relationship between farm size and GHG emissions, the study revealed that the impact of agricultural policies, technological advancements in agricultural machinery, and management practices on GHG emissions became progressively evident with increasing farm size, positing a potential non-linear progression of emis-

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sions. Therefore, the linear regression analysis presented earlier uncovered a discontinuous pattern, initially facilitating an increase in emissions before transitioning to a suppressive phase. In response to these dynamics, this research devised an advanced non-linear model (4), which integrated the squared term of farm size (farm area) to refine model (3). Model (4) retained the same set of variables as its predecessor, introducing Sln*far* as the squared term of ln*far*. An examination of the regression outputs detailed in Table 3, particularly the first and third columns, elucidated a distinct pattern: the coefficients pertaining to ln*far* as base explanatory variables were markedly positive, while those correlated with the squared term manifested a negative trajectory. This analysis substantiated the existence of an inverted U-shaped relationship between farm size and GHG emissions. As farm size increased, both the emission intensity and *per capita* emissions initially escalated before demonstrating a downturn, depicting a bell-shaped curve.

Refining the articulation of GHG emission dynamics based on farm size, we observed that below the threshold of 0.58 km² (870 mu), farm expansion was associated with elevated GHG emission intensity. During this nascent phase, the methods deployed for pesticide and fertiliser application were unsophisticated, and the extent of irrigation was limited. Investment in farm management and technological infrastructure was generally modest, with infrastructure such as roads remaining underdeveloped. Concurrently, local government priorities may skew towards economic growth, potentially overshadowing environmental considerations. Paired with a more relaxed environmental oversight, this period was characterised by increased GHG emission intensity, correlated with concurrent growth in agricultural scale and the imperative of enhanced food production. Upon exceeding the farm size threshold of 0.58 km², a reduction in GHG emission intensity was observed with additional expansion. This transition signified a shift towards mature agricultural practices that balance productivity with environmental stewardship. Enhanced techniques in nutrient management, irrigation, and farm operation were implemented, supported by increased investment in infrastructure and roads. Policy influence became evident, promoting sustainable input use and energy sources. Market forces and strict environmental policies drove farms towards greater efficiency, leading to lowered GHG emissions.

Per capita GHG emissions exhibited a trend of initially increasing and then decreasing, with a turning point at 0.69 km². The critical value of farm population agglomeration on GHG emissions per unit area was lower than the effect of farm population agglomeration on *per capita* GHG emissions, suggesting that the GHG emission effect brought on by an increase in farm size first reduced the intensity of farm GHG emissions, and then the intensity of *per capita* emissions

Table 3. Estimation of non-linear model

Variable	(1) *gei*	(2) *gei*	(3) *pge*	(4) *pge*
ln*far*	1.1532 (2.3738)**	0.7532 (4.826)***	1.2136 (5.2938)***	0.8766 (3.3246)***
Sln*far*	−0.0352 (−2.0283)**	–	−0.0652 (−2.4829)**	–
ln*edev*	0.1723 (1.9638)**	0.1541 (2.3283)**	0.1821 (2.1023)**	0.1632 (2.1672)**
Sln*edev*	−0.0412 (−2.0283)**	−0.0762 (−2.0283)**	−0.0762 (−2.0283)**	−0.0582 (−2.0283)**
ln*pes*	0.1352 (3.2793)***	0.1762 (4.2304)***	0.1425 (5.8634)***	0.1354** (3.9353)***
ln*fer*	0.1622 (3.2394)***	0.1724 (2.1832)**	0.1452 (4.2345)***	0.1524 (1.9746)**
ln*irri*	0.0928 (0.7553)	0.0725 (1.2874)	0.0815 (1.0728)	0.0775 (0.9723)
ln*agm*	−0.0812 (−1.9820)**	−0.0911 (−1.2474)*	−0.0798 (−2.4937)**	−0.0892 (−2.7532)**
ln*mle*	−0.1016 (−1.9729)**	−0.0974* (−2.4389)**	−0.1013** (−3.1819)***	−0.8295* (−3.4983)***
apol	−0.1438 (−5.2983)***	−0.1873** (−4.4526)***	−0.2011** (−4.2235)***	−0.1097** (−3.9473)***
*size*1 × ln*far*	–	−0.4062 (−2.8656)***	–	−0.4154 (−3.0635)***
*size*2 × ln*far*	–	−0.8405 (−1.9864)**	–	−0.9789 (−1.9702)**
*size*3 × ln*far*	–	−1.2348 (−2.0149)**	–	−1.5289 (−2.2961)**
*size*4 × ln*far*	–	−0.7999 (−2.4227)**	–	−0.9637 (−3.0153)***
_cons	5.2321 (8.392) ***	3.6876 (9.2308) ***	4.5231 (10.5022) ***	4.3875 (8.3973) ***
R^2	0.8012	0.9126	0.8907	0.8903

*, **, *** significant at 10%, 5%, and 1% level, respectively; the significance levels are denoted using *T* statistics, presented in parentheses; *gei* – GHG intensity per ha, encapsulating the emissions produced per km² of farm area; *pge* – *per capita* GHG emission intensity, *far* – farm area; Sln*far* – squared term of ln*far*; *edev* – economic development level; Sln*edev* – quadratic term of ln*edev*; *pes* – pesticide; *fer* – fertiliser; *irri* – irrigation; *agm* – agricultural machinery; *mle* – management level; *apol* – agricutural policy; *size*1, *size*2, *size*3, *size*4 – categorical variables for four different farm-size categories (family-sized farms, medium-sized farms, large-sized farms, super-sized farms, respectively); *_cons* – constant term
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decreased. To a certain extent, it shows that it is more difficult to reduce *per capita* GHG emissions from farms than to reduce GHG emissions per unit area. Therefore, this rule should be observed in the creation of agricultural emission reduction programs to gradually promote the reduction of GHG emissions.

Moreover, this study categorised farm sizes into five categories according to the extent of farmland, conducting non-linear regression analysis to compare updated results with previous findings. Utilising small farms as a baseline, four dummy variables representing different farm sizes were established. To forge a new non-linear model (5), four interactive terms involving these dummy variables and farm sizes were integrated into model (3). Within this advanced model, farm size multipliers were coupled with dummy variables, signified by the terms $size_{it,k}$ and lnpsi_{it}, $size_{it,k}$. Remaining factors were aligned with those in model (3). The deduced outcomes are showcased in columns (2) and (4) of Table 3. The impact of farm size on GHG emission intensity in model (5) was captured by the coefficient $\gamma1 + \theta k$. To exemplify, examine the column (2) dataset: a farm size increment of 1% prompts a 0.753% rise in GHG emission intensity for small farms, while family farms saw a 0.347% increase. Contrastingly, medium-sized farms noted a 0.087% diminution in emission intensity per 1% farm expansion. Large farms similarly witnessed a 0.482% drop in emission intensity for each 1% size increase, and super farms exhibited a 0.047% decrease in emission intensity per 1% growth. Varying farm sizes had a bell-curved influence on GHG emission intensity, suggesting the lowest intensity occured at an intermediate farm size range of 0.45 km^2 to 0.58 km^2. The regression insights of column (4) mirror this bell-shaped trend, revealing a peak of *per capita* GHG emissions at a larger farm size than indicated in column (2). These non-linear patterns correspond with those discovered in model (4), reinforcing the idea of an optimal farm size for sustainable ecological progress, which is applicable both in terms of GHG emissions per unit area and *per capita*.

Table 4. Results of 2SLS estimation

Variable	(1) 2SLS-*gei*	(2) 2SLS-*gei*	(3) 2SLS-*pge*	(4) 2SLS-*pge*
ln*far*	1.2861 (3.2091)***	0.7565 (3.9837)***	1.3104 (4.0518)***	0.8788 (4.3291)***
Sln*far*	–0.0783 (–1.9691)**	–	–0.0983 (–1.7091)*	–
ln*edev*	0.1429 (2.0725)**	0.1534 (2.4491)**	0.1235 (1.6624)*	0.1566 (1.8603)*
Sln*edev*	–0.0436 (–2.1633)**	–0.0692 (–2.0731)**	–0.0832 (–2.4321)**	–0.0746 (–2.2721)**
ln*pes*	0.1350 (3.0325)***	0.1422 (4.2833)***	0.1294 (5.0916)***	0.0964 (3.2671)***
ln*fer*	0.1023 (3.8245)***	0.1076 (2.0334)**	0.0892 (1.9951)**	0.1182 (3.8615)***
ln*irri*	0.0992 (0.9246)	–0.0431 (–1.2832)	0.0897 (2.0972)**	–0.0856 (–1.5728)*
ln*agm*	–0.1393 (–2.5476)**	–0.0958 (–1.6501)	–0.1026 (–2.5792)**	–0.0962 (–1.7547)*
ln*mle*	–0.1239 (–3.2351)***	–0.1333 (–4.8038)***	–0.1017 (–2.9626)***	–0.1165* (–3.8291)***
apol	–0.1074 (–1.7351)*	–0.1539 (–2.2301)**	–0.1903 (–2.4982)**	–0.1027 (–1.8905)*
*size*1 × ln*far*	–	–0.4065 (–2.1582)*	–	–0.4166 (–1.8638)*
*size*2 × ln*far*	–	–0.8412 (–1.7469)*	–	–0.9793 (–1.9902)**
*size*3 × ln*far*	–	–1.2388 (–2.7413)***	–	–1.5301 (–1.9901)**
*size*4 × ln*far*	–	–0.8022 (–2.0478)**	–	–0.9643 (–1.7313)*
_cons	4.1275 (9.6014)***	3.5012 (8.7918)***	2.729 (10.1532)***	2.3755 (9.3613)***
R^2	0.8905	0.9216	0.8952	0.8841
The first stage of *F*-test	178.14	204.27	146.13	189.13
The second stage of *F*-test	80.24	99.15	80.43	70.98
Sargan-Hansen *P*	0.23	0.25	0.33	0.29

*, **, *** significant at 10%, 5%, and 1% level, respectively; the significance levels are denoted using *T* statistics, presented in parentheses; 2SLS – two-stage least squares; *gei* – GHG intensity per ha, encapsulating the emissions produced per km^2 of farm area; *pge* – *per capita* GHG emission intensity, *far* – farm area; Sln*far* – squared term of ln*far*; *edev* – economic development level; Sln*edev* – quadratic term of ln*edev*; *pes* – pesticide; *fer* – fertiliser; *irri* – irrigation; *agm* – agricultural machinery; *mle* – management level; *apol* – agricutural policy; *size*1, *size*2, *size*3, *size*4 – categorical variables for four different farm-size categories (family-sized farms, medium-sized farms, large-sized farms, super-sized farms, respectively); *_cons* – constant term
Source: Adapted from Hu and Fan (2020)

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Regression analysis of instrumental variables

The relationship between farm size and GHG emissions might be subject to endogenous biases. To address these issues in the regression analysis, the use of instrumental variable estimation is essential. The study introduced controls for fixed effects to alleviate concerns about collinearity within the regression framework. This framework included the use of instrumental variables. The estimations obtained using the two-stage least squares (2SLS) technique are presented in Table 4, showcasing the refined analysis outcomes.

Upon analysing the first-stage regression outcomes, the computed *F*-statistic substantially exceeded the critical value, thereby eliminating concerns about weak instrumental variables. So, if highway proximity was considered an instrumental variable, there seemed to be no direct association with farm size. Additionally, the non-significant Sargan-Hansen statistic led us to maintain the null hypothesis that the external instrumental variables did not exert influence, which confirmed the validity of the chosen road instrumental variable. Further, second-stage regression indicated a non-linear relationship between farm size and GHG emissions; both emission intensity and *per capita* emissions initially rose and then declined with an increasing farm area. Crucially, the consistency of the regression coefficients for farm size with those documented in Table 3 underscored the robustness of the established correlation, unaffected by any notable discrepancies.

Robustness test

Since 2019, the Chinese government has initiated a suite of initiatives designed to reduce emissions from agriculture, marking significant strides towards green proliferation in the agricultural and rural domains. Mindful of the potential for these extensive policy measures to introduce bias into the previously delineated regression outcomes, this paper segmented the aggregate dataset to be used in the 2SLS regression analysis into two distinct cohorts, designating them as subsample 1 (pre-2019) and subsample 2 (post-2019). Table 5 breaks down the regression results, with columns (1) to (4) poring over subsample 1's data and columns (5) to (8) dissecting the regression details correlative to subsample 2. The analyses revealed critical insights: farm size, its square, the

Table 5. Results of 2SLS estimation for subsamples

Variable	Subsample 1				Subsample 2			
	(1) 2SLS-*gei*	(2) 2SLS-*gei*	(3) 2SLS-*pge*	(4) 2SLS-*pge*	(5) 2SLS-*gei*	(6) 2SLS-*gei*	(7) 2SLS-*pge*	(8) 2SLS-*pge*
ln*far*	1.2143 (2.1872)**	0.7589 (3.872)***	1.2873 (1.9361)*	0.8772 (2.231)**	1.1343 (2.4367)**	0.7592 (3.0326)***	1.2869 (2.1307)**	0.8792 (4.1017)***
Sln*far*	–0.0892 (–2.131)**	–	–0.0942 (–1.733)*	–	–0.0762 (–1.692)*	–	–0.1092 (–2.135)**	–
*size*1 × ln*far*	–	–0.4088 (–2.133)**	–	–0.4172 (–1.986)*	–	–0.4092 (–2.472)**	–	–0.4199 (–2.278)**
*size*2 × ln*far*	–	–0.8471 (–1.852)*	–	–0.9761 (–1.892)*	–	–0.8482 (–2.421)**	–	–1.0122 (–3.827)***
*size*3 × ln*far*	–	–1.2382 (–1.932)*	–	–1.5255 (–2.309)**	–	–1.2383 (–3.915)***	–	–1.5329 (–2.328)**
*size*4 × ln*far*	–	–0.8072 (–1.837)*	–	–0.9692 (–2.457)**	–	–0.8083 (–3.872)***	–	–0.9681 (–3.537)***
Control	yes	yes	yes	yes	yes	yes	yes	yes
_*cons*	4.2321 (8.897)***	3.3829 (9.137)***	4.3204 (7.432)***	4.8231 (8.159)***	2.0324 (7.805)***	3.2912 (9.842)***	2.9912 (10.145)***	4.0293 (9.816)***
R^2	0.8905	0.9172	0.9216	0.8623	0.9817	0.9452	0.9172	0.8962

*, **, *** significant at 10%, 5%, and 1% level, respectively; the significance levels are denoted using *T* statistics, presented in parentheses; 2SLS – two-stage least squares; *gei* – GHG intensity per ha, encapsulating the emissions produced per km^2 of farm area; *pge* – *per capita* GHG emission intensity, *far* – farm area; Sln*far* – squared term of ln*far*; *size*1, *size*2, *size*3, *size*4 – categorical variables for four different farm-size categories (family-sized farms, medium-sized farms, large-sized farms, super-sized farms, respectively); _*cons* – constant term

Source: Adapted from Bekun and Alola (2022)

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farm size interaction term, and all four categorical variables exhibited statistically significant regression coefficients. The striking stability in these coefficient values indicated that the relationship between farm size and GHG emissions persisted, tracing an inverted U-shape, even in the presence of agricultural policy implementations.

Previously, empirical investigations have primarily represented farm size in terms of farm area. The characterisation of farm size can include not only the farm area but also the number of farmers, denoted as *pfa*. This study examined the potential inaccuracies that might arise from using *pfa* as a proxy for farm size, considering a variety of measurement indices. The results from the 2SLS regression analysis, which positioned *pfa* as the key explanatory variable, are detailed in Table 6. The correlation coefficients featured in Table 6 show a moderate decrease relative to those in Table 4, indicating that the expansion of farm area had a more significant influence on GHG emissions compared to variations in *pfa*. This empirical evidence suggested that increasing farm area up to a certain threshold may help achieve GHG emission reduction goals. It further clarified that when farm size reached an optimal level, both the intensity of GHG emissions and *per capita* GHG emissions declined, highlighting the crucial balance between farm scale and environmental impact.

Table 6. Estimation outcomes with 2SLS method using agricultural population of farm as proxy variable

Variable	(1) 2SLS-*gei*	(2) 2SLS-*gei*	(3) 2SLS-*pge*	(4) 2SLS-*pge*
ln*pfa*	1.1052 (4.3124)***	0.4302 (6.1093)***	0.9222 (3.0518)***	0.5233 (2.9032)***
Sln*pfa*	−0.0672 (−2.3629)**	–	−0.0362 (−1.9656)**	–
*size*1 × ln*far*	–	−0.1045 (−1.8656)*	–	−0.1840 (−2.3012)**
*size*2 × ln*far*	–	−0.4667 (−2.3414)*	–	−0.5863 (−2.9362)***
*size*3 × ln*far*	–	−0.7028 (−1.7043)*	–	−1.1762 (−1.4026)
*size*4 × ln*far*	–	−0.5019 (−2.2518)**	–	−0.4992 (−2.5163)**
Control	yes	yes	yes	yes
_cons	4.2319 (7.337)***	3.6782 (8.192)***	3.2802 (9.832)***	4.2422 (9.184)***
R^2	0.8938	0.8299	0.8901	0.9253

*, **, *** significant at 10%, 5%, and 1% level, respectively; the significance levels are denoted using *T* statistics, presented in parentheses; 2SLS – two-stage least squares; *gei* – GHG intensity per ha, encapsulating the emissions produced per km^2 of farm area; *pge* – *per capita* GHG emission intensity; *pfa* – population of the farm in units of 10 000 people; Sln*pfa* – squared term of ln*pfa*; *far* – farm area; *size*1, *size*2, *size*3, *size*4 – categorical variables for four different farm-size categories (family-sized farms, medium-sized farms, large-sized farms, super-sized farms, respectively); *_cons* – constant term

Source: Adapted from Bekun and Alola (2022)

DISCUSSION

In pursuit of emission reduction goals within China, the challenge of controlling GHG emissions from agricultural activities has come to the forefront. Strategic adjustments to farm sizes can lead to lower GHG emissions both in terms of intensity from agricultural operations and on a *per capita* basis while also facilitating the development of eco-friendly farming practices. The dynamic between farm size and GHG emissions was identified as an inverted U-shaped curve, aligning with the findings of carbon emissions in Chinese planting (Li et al. 2023). Yet, studies such as those by Zhu et al. (2022) underlined that larger farming operations can offer improved fertiliser use efficiency, curbing the environmental degradation caused by fertiliser overuse. This paper arrived at a distinct conclusion by considering a broader array of factors beyond merely the influences of fertilisers.

Currently, the Chinese agricultural landscape is dominated by small farms. As of late 2021, the country has more than 3.8 million family farms, with an average size of 134.3 acres. This accords with this study's findings that suggest an optimal farm size ranging between 0.45 km^2 and 0.58 km^2. Thus, promoting the development of farms within this optimal size range can lead to a better allocation of resources, including management techniques, technology, irrigation systems, organic fertilisers, and infrastructure like roads. This approach not only supports the establishment of ecological farms but also mitigates environmental detriments.

The government should align its emission reduction strategies with GHG legislation, aiming to lower the intensity of GHG emissions and *per capita* emissions. To meet emission reduction objectives, the preferred strategy should involve cautiously expanding farm size rather than simply increasing the number of individuals employed in agriculture. This recommendation is essential for balancing agricultural productivity with environmental conservation.

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CONCLUSION

Conclusions and limitations. Mitigating GHG emissions in agriculture, both in intensity and *per capita* terms, is imperative for fostering a greener, low-carbon shift and ensuring sustainable agricultural development. This study delved into the theoretical dynamics linking farm size with GHG emissions, constructed an econometric framework using Chinese agricultural GHG emissions and farm size data, and validated the robustness of its findings through instrumental variables regression. The research uncovered an inverted U-shaped relationship between the escalating scale of farms and GHG emissions. Farms of a moderate scope demonstrated lower levels of both GHG emission intensity and *per capita* GHG emissions. Subsequent non-linear regression analyses, segmented by farm size, pinpointed an optimal emission reduction zone within the range of 0.45 km^2 to 0.58 km^2. Moreover, a comparative inquiry into the influence of two predominant variables (farm size and agricultural workforce numbers) divulged a more pronounced impact of farm size adjustments on mitigating GHG emissions rather than *per capita* emissions, highlighting the greater challenge of attenuating *per capita* emissions from farms as opposed to area-specific emissions.

Constrained by the data and methodological scope of the study, the current analysis was limited to a provincial perspective on the correlation between farm size and GHG emissions. It left the dynamics at the municipal level unexplored. Future research could expand the inquiry to capture the intricacies of the farm size-GHG emissions nexus at the city or county levels, offering a more detailed and robust foundation to guide policies aimed at achieving the dual carbon goals.

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