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Impact of the rural digital economy on livestock carbon emissions and pollution mitigation in China

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KEYWORDS

Carbon emissions, digital economy, green technology progress, livestock environmental pollution, resource allocation efficiency, spatial effect

HIGHLIGHTS

- The rural digital economy promotes synergistic control of livestock carbon emissions and environmental pollution (SCLCP).
- It works through green technology progress, resource allocation efficiency improvement and production agglomeration.
- Government support amplifies the positive effects in agricultural and agropastoral transitional zones.
- However, marketization weakens the environmental benefits of the rural digital economy in agricultural zone.
- The influence of the rural digital economy on SCLCP demonstrates significant spatial spillover effects.

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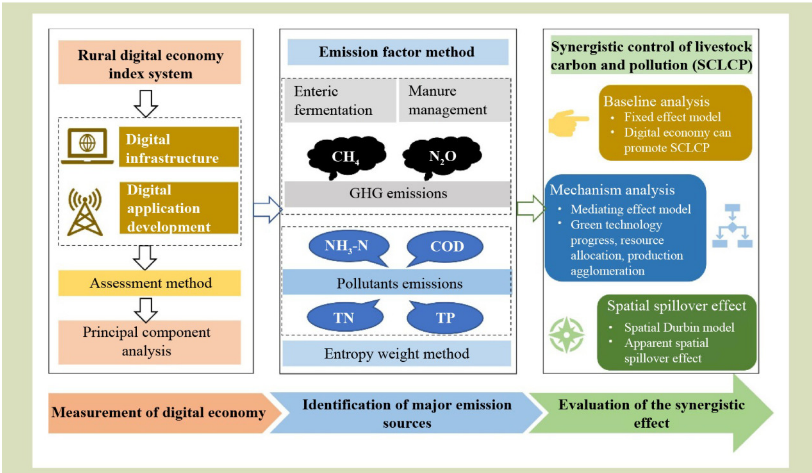
GRAPHICAL ABSTRACT



ABSTRACT

The synergistic control of livestock carbon emissions and environmental pollution (SCLCP) is essential for the sustainable development of animal husbandry. Using panel data from the provincial level in China from 2011 to 2021, this study empirically examined the effect of the rural digital economy on livestock carbon emissions and pollution mitigation. Four key findings are given. First, the rural digital economic significantly facilitates the synergistic control of livestock carbon emissions and pollution, with robustness confirmed through instrumental variable approaches and other robustness tests. Second, mechanism analysis revealed that the rural digital economy can promote SCLCP through green technology progress, resource allocation efficiency improvement and production agglomeration. Third, heterogeneity analysis indicates that government support would further strengthen the effect of the rural digital economy on SCLCP, and this impact mainly occurs in agricultural zone and agropastoral transitional zone. In contrast, marketization weakens this effect in agricultural zone. Finally, spatial econometric analysis demonstrated that the rural digital economy can reduce livestock carbon emissions in neighboring areas, with marketization exerting a positive moderating effect, while government support had no significant moderating effect. Additionally, the spatial spillover effect of the rural digital economy on livestock-related environmental pollution was not significant.

1 Introduction

With rising incomes and the upgrading of the consumption structure, the demand for livestock products is increasing rapidly. Evidence shows that 80% of the increase in global meat production over the next decade will occur in low and middle-income countries[1]. Simultaneously, non-CO_2 greenhouse gas emissions from livestock intestinal fermentation and manure management have become a major threat that accelerates climate change[2]. Also, the adverse impact of water pollutants from livestock manure excrement on the environment and human health is increasingly evident[3]. Livestock production pollution accounts for 74% to 88% of river nutrients and oocyst pollutants[4]. Therefore, achieving synergistic control of livestock carbon emissions and environmental pollution (SCLCP) while ensuring production is vital. The rise of the digital economy offers new opportunities for addressing environmental issues[5]. Driven by information networks and digital technology, digital economic growth can reduce information asymmetry, promote production method changes and improve resource allocation efficiency, thereby alleviating the environmental redundancy problem brought by resource waste or scarcity[6,7].

In recent years, the relationship between the digital economy and environmental performance has gradually become a research strong focus; however, the views are inconsistent. The first view is that the digital economy can reduce carbon emissions[8,9]. Ulucak et al.[10] found that information and communication technologies have a positive impact on carbon emission reduction. The second view holds that the digital economy will further exacerbate carbon emissions[11]. Relevant studies have indicated that the development of the local digital economy would induce polluting industries to transfer to neighboring areas, thus increasing carbon emissions in the neighboring regions[12]. The third view suggests a nonlinear relationship between digital economy and carbon emissions. Zheng et al.[13] noted that when the digital development level reaches a mature stage, its impact on carbon emissions will change from promoting to inhibiting. In contrast, Ahmadova et al.[14] argued that there is an inverted U-shaped relationship between the digital economy and environmental performance; an excessively high level of digital economy will lead to a rebound effect, resulting in higher pollution emissions. In addition, some studies have focused on the relationship between the digital economy and the collaborative control of carbon emissions and pollution[15]. For example, Hu[16] analyzed the impact of setting up Big Data integrated pilot areas on air pollutants and carbon emissions and found that these led to lower carbon emissions and pollution emissions.

In addition, a few studies have discussed the relationship between the digital economy and agricultural environmental performance[17]. Scholars point out that the digital economy can reduce the agricultural carbon emissions intensity by promoting agricultural technology inputs, human capital level and urbanization rate[18]. However, no existing reports has discussed the relationship between the digital economy and environmental performance in animal husbandry. Most studies involving the environmental performance of animal husbandry focus on carbon emission measurement[19–21], pollution measurement[22,23], analysis of influencing factors[24] and effect evaluation[25,26]. Also, scholars demonstrated that the environmental performance of animal husbandry is mainly influenced by green technology innovation[27], environmental regulation[28], industrial structure[29], rural financial development[30] and consumption patterns[31].

However, few studies have directly analyzed the relationship between the rural digital economy and synergies control of livestock carbon emissions and environmental pollution. Previous studies on the digital economy and environmental performance mainly focus on the secondary and tertiary industries, and there is a notable lack of empirical research linking the digital economy to animal husbandry. In addition, a research gap remains in the existing literature in terms of mechanism analysis and spatiotemporal dependent effect through which the digital economy affects SCLCP, as well as the heterogeneous characterization of the impact of digital economy. Therefore, this study examined the impact mechanism and spatial effects of the rural digital economy on livestock carbon emissions and pollution mitigation to determine if the digital economy helps achieve SCLCP, with green technology progress, resource allocation efficiency and production agglomeration as mechanism variables. Also, this research explored the role of government support and marketization between the rural digital economy and SCLCP.

This study contributes to the existing literature in the following three aspects. First, we developed an integrative and empirical view by verifying that the rural digital economy has positive impact on livestock carbon emissions and pollution mitigation. It gives a potential academic contribution to the economic theory of the relationship between the digital economy and environmental performance, and thus fills the research gap of the digital economy in the field of environmental governance of animal husbandry; Second, we investigated the indirect mechanism for the rural digital economy to SCLCP through three channels: green technology progress, resource allocation efficiency and production agglomeration. We further analyzed the regulatory impact of government support and marketization on SCLCP. These provide an important theoretical and practical basis for promoting the full coupling of the rural digital economy and modern animal husbandry development. Third, we extended previous work that the digital economy development affects national environmental performance by incorporating spatial dependency analysis. We examined this impact in the framework of spatial effect analysis. Currently, the dividends unleashed by the rural digital economy in livestock production are insufficient, resulting in difficulties in implementing policy recommendations, pathway choices and policy references regarding smart animal husbandry. Therefore, clarifying the specific impact of the rural digital economy on the green development of animal husbandry and its mechanism will help guide government environmental and digitalization policies for animal husbandry.

Below, we provide a theoretical analysis and research hypotheses, and describe the study methods and data description, and the results. Finally, the possible policy recommendations of the main findings are given.

2 Theoretical analysis and research hypotheses

2.1 The direct impact of the rural digital economy on SCLCP

The rural digital economy has the potential to promote the green development of animal husbandry. First, from the perspective of production, the elements of the rural digital economy are continuously penetrating agricultural production. Accelerating information dissemination and alleviating information asymmetry between supply and demand entities, effectively reduces the information costs of production and improves market transaction efficiency[32]. In addition, the application of digital intelligent devices and technologies helps analyze livestock production environments, adjust management methods adaptively, and scientifically and reasonably plan layouts, promoting refinement and standardization of various stages of livestock production. This maximizes the efficiency of resource allocation, mitigates the contradictions between production and the environment, and promotes the greening of livestock production. Second, from the perspective of consumption, as material conditions improve, consumer demand has shifted from quantity to quality. The frequent occurrence of food safety problems has deepened consumer demand for high-quality, ecologically healthy and green food. The core step of digital agriculture innovation and reform is to focus on consumer demand, achieve communication and interaction between consumers and producers, promote new sales models, and force producers to examine efficient, safe, and environmentally friendly ecological farming models[33], thereby promoting carbon emissions and pollution mitigation in animal husbandry. Accordingly, we propose our first hypothesis.

H1: Rural digital economy helps the synergistic control of livestock carbon emissions and environmental pollution.

2.2 The indirect impact of the rural digital economy on SCLCP

Combined with the direct effect analysis and the core features of the digital economy, it is found that the development of the digital economy promotes SCLCP mainly through three aspects: green technology progress, resource allocation and production agglomeration.

First, green technology progress is key driving force for achieving green transformation of animal husbandry, while the rise of the digital economy injects fresh vitality into the progress of green technologies. Based on universality and sustainability, digital technology can permeate and integrate into current livestock production technologies, enabling *disruptive* technological innovations. By intelligently transforming key components, such as precise feeding, environmental control, waste management and product collection, resource use efficiency can be improved, facilitating the transition of livestock production toward greener methods[34]. For example, the introduction of intelligent feeding systems, automated waste cleaning devices and smart monitoring equipment in animal husbandry can replace the current practice of manual feeding and waste management techniques, resulting in better resource efficiency and reduced pollution[35]. Also, digital technology exhibits strong knowledge spillover effects[36]. This facilitates the aggregation of technological talent and data information at a regional, or even international level, lowering information and regional barriers in green technology research and development. This is conducive to strengthening cooperation, communication and collective learning among research entities, optimizing the human capital structure. Additionally, the deep integration of digital technology with existing financial services provides a reliable source of financing for green technological innovation, reducing both the risks and sunk costs associated with green technology R&D, and improving innovation efficiency among micro-entities to achieve SCLCP. Based on the above theoretical analysis, we propose our second hypothesis.

H2: Rural digital economy can promote SCLCP through the green technology progress effect.

Second, the fundamental contradiction between economic growth and environmental improvement depends on the structure and efficiency of various production factors. In the non-digital economy era, animal husbandry often faced challenges such as low information accessibility and outdated farming techniques, leading to obstacles in circulation, scarcity or waste of production factors[37]. With the advent of the digital era, the digital economy can penetrate the livestock sector through digital technology, data information and digital infrastructure, removing barriers to factor mobility and improving existing factor allocation methods, thereby promoting the transformation and upgrading of the animal husbandry[6]. Specifically, data, as a new production factor, possesses attributes such as derivativeness, sharing, non-competitiveness, and mobility. By integrating with the existing factors, such as labor and capital, it is advantageous for leveraging the additive value and synergistic effects of factor integration, enabling the restructuring of resource allocation systems and transformation of production modes[38]. With optimized adjustments to the input factor structure, production efficiency is enhanced, thereby reducing the carbon emissions and pollution emissions of animal husbandry. Additionally, the use of digital networks and information facilitates the construction of an information network system covering the entire process of livestock production, processing and marketing. This not only reduces resource misallocation caused by supply-demand mismatches, but also attracts capital, technology and talent from both upstream and downstream sectors, alleviating environmental issues arising from factor scarcity and excessive supply. Therefore, we propose our third hypothesis.

H3: Rural digital economy can promote SCLCP by improving resource allocation efficiency.

Third, to continuously reduce environmental pollution and carbon emissions in animal husbandry, it is necessary to leverage the economies of scale resulting from industrial agglomeration. The development of the rural digital economy promotes the continuous integration of modern information technologies such as the Internet, Big Data and artificial intelligence with the livestock industry. This integration provides livestock farming entities with richer digital elements, innovative resources and integrated service capabilities. It fosters resource sharing, cost reduction, risk diversification, innovation and knowledge diffusion, creating a favorable environment for production agglomeration. With the continuous improvement of the agglomeration level of animal husbandry, the scale economy effect of industrial agglomeration gradually emerged[39]. This leads to the formation of specialized and organized large-scale operations, with increased investment in environmental infrastructure such as waste management equipment. Consequently, the pressure on ecological resources is relieved. Additionally, the virtual agglomeration generated by the rural digital economy can alleviate the congestion effects caused by excessive geographical agglomeration, allowing economic entities to engage in transactions through virtual space and mitigate the congestion effects resulting from excessive agglomeration. Based on the above theoretical analysis, we propose the following hypotheses.

H4: Rural digital economy can promote SCLCP through the economies of scale of production agglomeration.

2.3 Spatial spillover effect of the rural digital economy on SCLCP

Due to the absence of geographical constraints, the efficient information transmission function of the rural digital economy enhances the interconnection and interaction of livestock production activities between regions. Specifically, the advanced information technologies involved in the rural digital economy can transcend organizational boundaries to promote the spread of green production technologies and environmental policies in animal husbandry. Neighboring regions learn from local technological innovations and environmental governance practices, developing suitable environmental governance tools that facilitate pollution reduction and carbon mitigation in animal husbandry. Also, with the help of digital platforms and digitized media, trade barriers between regions are broken, enabling fast cross-regional flow and sharing of production factors such as labor and capital[40]. This not only brings more digital financial support to livestock production in neighboring regions but also alleviates the problems of resource scarcity or redundancy that hinder production efficiency. This further promotes the green development of animal husbandry in the neighborhood.

However, research also indicates that the rural digital economy may generate negative spillovers[14]. Regions with economic or geographical proximity may experience resource competition, leading to the flow of production factors and green technologies toward regions with a higher level of the rural digital economy. This hinders the synergistic advancement of local livestock pollution reduction, carbon mitigation, and economic growth. Based on this, we propose our fifth and final hypothesis.

H5: Through the spatial spillover effect, local digitization can affect the environmental performance of animal husbandry in neighboring areas.

3 Methodology and data

3.1 Model

First, to reveal the impact of the rural digital economy on livestock carbon emission and environmental pollution, the panel fixed effect model was constructed as:

$$Y_{it} = \alpha_0 + \alpha_1 Digital_{it} + \sum \alpha_2 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

where, Y_{it} is the carbon intensity and pollution intensity from animal husbandry for province i in year t, $Digital_{it}$ is the development level of the rural digital economy for province i in year t, Z_{it} is all the control variables, μ_i is the regional-fixed effect. δ_t is the year-fixed effect, and ε_{it} is the random error item. α_0 is the constant term, α_1 is the parameter to be estimated for the rural digital economy, and α_2 is the parameter to be estimated for control variables.

Then, to further examine the mechanism of the rural digital economy development on livestock carbon emission and environment pollution, the following mechanism analysis model[41] is constructed as:

$$Med_{it} = \beta_0 + \beta_1 Digital_{it} + \sum \beta_2 Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

where, Med_{it} is the mechanism variable. β_0 is the constant term, β_1 is the parameter to be estimated for rural digital economy, and β_2 is the parameter to be estimated for control variables. The rural digital economy has an impact on the mechanism variable if the coefficient β_1 is significant.

In addition, considering the spatial spillover effect of the rural digital economy development on livestock carbon emission and environment pollution, we further constructed a spatial econometric model as:

$$\begin{aligned} Y_{it} = {} & \gamma_0 + \rho \sum_j w_{ij} Y_{j,t} + \gamma_1 Digital_{it} + \gamma_2 Z_{it} + \gamma_3 \sum_j w_{ij} Digital_{jt} \\ & + \gamma_4 \sum_j w_{ij} Z_{jt} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where, γ_0 is the constant term, and γ_1 and γ_2 are the coefficients of the rural digital economy and control variables, respectively. ρ is the spatial autoregressive coefficient and w_{ij} is the spatial weight matrix. This study selected the geographical adjacency matrix ($w(a)$) and the economic geography matrix ($w(e\text{–}g)$) for regression to improve the robustness of the results. γ_3 and γ_4 are the elastic coefficients of the rural digital economy and the interaction terms of the control variables.

3.2 Variables

3.2.1 Explained variables

Carbon intensity of animal husbandry (AHCEI). It is the ratio of total livestock carbon emissions to the output value of animal husbandry. Based on the *Guidance for Measurement, Reporting and Verification of Livestock Greenhouse Gases*

Emissions[42], we used the IPCC emission factor method to measure CH_4 and N_2O emissions from enteric fermentation and manure management of 11 types of livestock and poultry, taking into account factors such as the feeding cycle and scale of intensive farming. Also, CH_4 and N_2O were uniformly expressed in CO_2 equivalents using GWP100-AR6[43]. It should be noted that some scholars use the life cycle assessment method to calculate livestock carbon emissions[2,44]. However, due to limited provincial data availability and substantial fluctuations in the standard deviation of the default emission factor, carbon emissions estimated by the extended industrial chain cannot accurately reflect the current situation of carbon emissions in animal husbandry in China[45]. The assessment model for AHCEI is as:

$$E_{ef,i} = \sum_r (APP_{i,r} \times EF_{ef,r}) \times 27.9 \tag{4}$$

$$E_{mm,i} = \sum_r (APP_{i,r} \times EF_{mc,r}) \times 27.9 + \sum_r (APP_{i,r} \times EF_{md,r}) \times 273 \tag{5}$$

$$AHCEI_i = \frac{CE_i}{O_i} = \frac{E_{ef,i} + E_{mm,i}}{O_i} \tag{6}$$

where, $E_{ef,i}$ is the CO_2 emission from enteric fermentation in province *i*, $APP_{i,r}$ is the average annual stocking of livestock type r, $EF_{ef,r}$ is the emission factor for enteric fermentation of livestock type r, $E_{mm,i}$ is the CO_2 emission from manure management systems, $EF_{mc,r}$ and $EF_{md,r}$ are the CH_4 and N_2O emissions from manure management system, respectively. $AHCEI_i$ is the carbon intensity of animal husbandry, CE_i is the total carbon emissions from animal husbandry, and O_i is the gross value of animal husbandry output.

Pollution intensity of animal husbandry (AHPEI). It is a comprehensive index of pollution emissions intensity obtained by standardizing the discharge intensity of various water pollutants from animal husbandry. According to the statistical standard of animal husbandry pollutants in China, four kinds of water pollutants, chemical oxygen demand (COD), ammonia nitrogen (NH_3-N), total nitrogen (TN), and total phosphorus (TP), were considered in this study. To calculate pollutant discharges accurately, we referred to the *Manual of Agricultural Pollution Source Emission Coefficients*. The pollutant discharge coefficient of the manual takes into account the comprehensive impact of production characteristics and management conditions in different regional and animal feeding cycles on pollutant emissions, which can reflect the actual emissions of animal pollution rather than the pollutant production capacity. AHPEI is calculated as:

$$Pollution_{i,t}^{h} = \sum_r \left(APP_{i,t}^{r} \times ef_{i,t}^{r,h} \times 365\right) \tag{7}$$

$$AHPEI_{i,t}^{h} = \frac{Pollution_{i,t}^{h}}{O_i} \tag{8}$$

where, $Pollution_{i,t}^{h}$ is the actual pollutants emissions of various livestock in province *i*, *h* = 1, 2, 3 and 4 respectively represent four types of water pollutants (COD, NH_3-N, TN and TP), and $ef_{i,t}^{r,h}$ is the daily pollutant discharge coefficient for *r* types of livestock and *h* types of pollutants. $AHPEI_{i,t}^{h}$ is the pollution intensity of animal husbandry. Finally, the entropy weight method is used to weight the emission intensities of the four types of pollutants, resulting in the total emission intensity of pollutants from animal husbandry.

Figure 1 shows the distribution features of AHCEI and AHPEI for Chinese provinces in 2011 and 2021. The AHCEI and AHPEI have prominent characteristics of being high in the west and low in the east, high in the north and low in the south, and decreasing yearly. Specifically, from 2011 to 2021, the average carbon emissions intensity of animal husbandry in China fell from 3.71 to 2.33 t per 10,000 yuan, with an average annual rate of decline of 4.51%. The average pollution intensity of animal husbandry in China dropped from 0.473 to 0.392, with an annual decline of 1.78%. The provinces with higher AHCEI and AHPEI are concentrated in the north-west and along the Great Wall of China, e.g., Qinghai and Xizang. This is likely due to the dominance of herbivorous livestock production in these areas, which generates higher carbon emissions and environmental pollution. In addition, compared with the southeast region, these regions are relatively backward in resource endowment and economic development level, which results in a relative scarcity of environmental governance facilities and green technology, thus facing tremendous pressure on animal husbandry to reduce carbon emissions and pollution.

3.2.2 Key explain variable

Rural digital economy development level (*Digital*). Referring to Yi et al.[46] and Tian et al. [7], we constructed an index system of the rural digital economy development composed of two primary indicators (digital infrastructure and digital application) and nine secondary indicators, as given in Table 1. Based on the index system, the principal component analysis, which can reduce the dimensionality of multiple indexes and avoid the error caused by subjective judgment[47], was used to measure the development level of the rural digital economy.

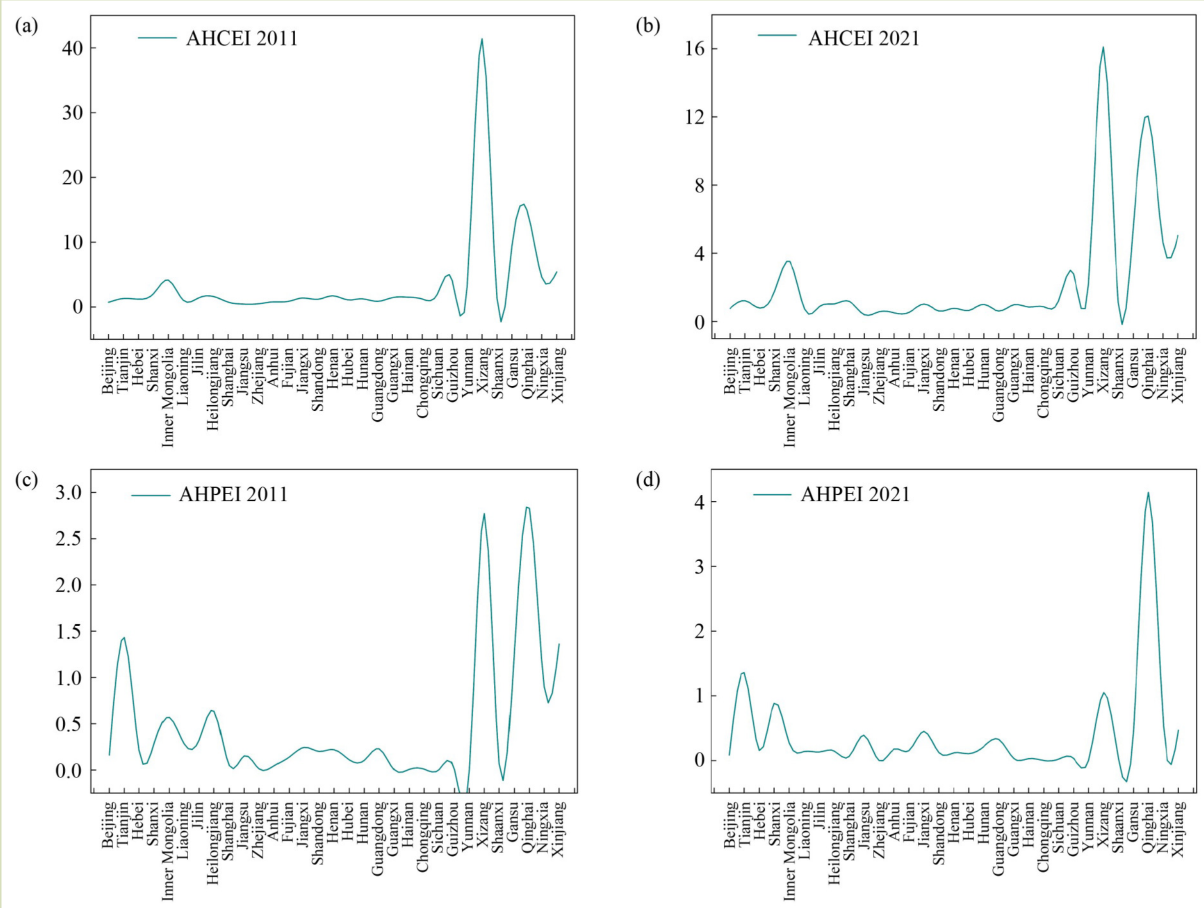


Fig. 1 Carbon intensity of animal husbandry (AHCEI) (a, b) and pollution intensity of animal husbandry (AHPEI) (c, d) in regions of China in 2011 and 2021.

Table 1 Index system of the rural digital economy development

Primary indicator	Secondary indicator
Digital infrastructure level	Computer ownership (per 100 rural households)
	Mobile phone ownership (per 100 rural households)
	Rural broadband Internet access users (10,000 households)
	Rural cable broadcast TV subscriber rate (%)
Digital application development capabilities	Number of agrometeorological observation stations (units)
	Total power of agricultural machinery (GW, i.e., gigawatt)
	Rural electricity consumption (TWh, i.e., terawatt hours)
	Number of Taobao villages (units)
	Rural Digital Financial Inclusion Index

Note: The criteria for identifying a Taobao Village mainly include the following: (1) Location: The business activities are based in rural areas, using administrative villages as the basic unit; (2) Sales scale: The annual e-commerce sales of the village reach at least 10 million yuan; (3) E-commerce activity: The village has at least 100 active online stores, or the number of active stores accounts for at least 10% of the total number of local households.

Based on the standard that the percentage of variance criterion should exceed 80% of the total variance, the first four principal components were selected, explaining 80.8% of the explanatory variables. For robustness test, we also used the entropy weight method to measure the development level of the rural digital economy.

Figure 2 shows the distribution of the rural digital economy for Chinese provinces. The rural digital economy development level has increased from 1.26 to 3.21 during 2011–2021 in China, with an average annual growth rate of 9.98%. From the perspective of provinces, the level of development of the rural digital economy in all provinces has retained a suitable momentum. In 2021, the provinces with higher development level of the rural digital economy mainly included Guangdong, Jiangsu, Zhejiang, Henan, Shandong and Hebei Provinces. Regions with relatively poor development level of the rural digital economy mainly included Inner Mongolia, Qinghai, Xizang, Ningxia and Hainan. In other words, rural digital economy development decreased from the eastern region to the western region. The possible reason is that the eastern regions generally have richer resources and infrastructure. In summary, the rural digital economy in China is developing rapidly but unevenly.

3.2.3 Mechanism variables

Green technology progress. Referring to Liu et al.[47], this study used an ML productivity index component containing undesirable outputs to measure green technology progress in animal husbandry.

Resource Allocation Efficiency. This study considers the utilization rates of labor, capital, and intermediate consumption. The use efficiency of each production factor is calculated using the input slack value and the target value of super-efficiency SBM. Finally, the entropy weight method measures the comprehensive resource allocation efficiency.

Production agglomeration. According to Billings and Johnson[48], a location quotient index based on output value is used to measure the production agglomeration of animal husbandry.

3.2.4 Control variables

We included some control variables referring to the previous research: (1) Agricultural fiscal expenditure intensity (*Gov*), measured by the proportion of agriculture-supporting funds in local financial expenditure. (2) Environmental regulation (*Reg*),

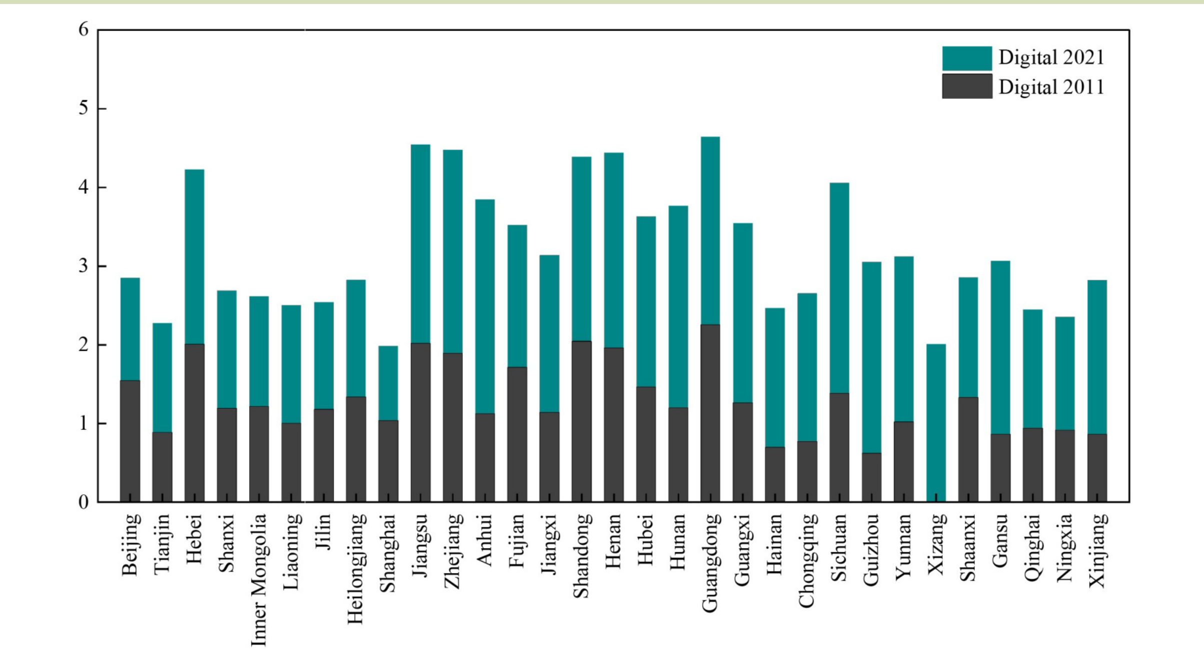


Fig. 2 Rural digital economy development level (digital) in regions of China in 2011 and 2021.

following Zeng et al.[49], we used the reciprocal distance between the regional center and the border of each province as an adjustment coefficient to account for regional economic development levels. (3) Feed production capacity (*Feed*), denoted by the logarithm of feed production for each province. (4) Quantity of labor force (*Labor*). Due to a lack of direct statistics on animal husbandry labor, we estimated the number of people employed in animal husbandry by multiplying the proportion of output value from animal husbandry by the total agricultural output value with the total number of laborers in agriculture as suggested by Han et al.[50]. (5) Educational level (*Edu*), which generally indicates the quality of the labor force. We used the natural logarithm of the average education years of the rural population to measure the education level. Specifically, this variable is the weighted average of the proportion of the population with different levels of education multiplied by the corresponding education years[51]. (6) Rural income level (*Income*). In this study, we used the proportion of per capita wage income of rural residents in the per capita disposable income of rural residents to reflect the income level of rural residents. (7) Regional economy development level (*Lngdp*), represented by the logarithm of per capita GDP. (8) Scientific research investment (*Scre*), measured by the logarithm of internal expenditure on research and development (R&D) from animal husbandry. It can reflect the innovation ability of green production technology in animal husbandry. (9) Animal husbandry structure adjustment (*Stru*). To reflect the impact of production structure adjustment in animal husbandry, we choose the proportion of the output value of herbivorous animal husbandry to the output value of pigs to measure the index.

3.3 Data

Considering data availability, this study used data from 2011 to 2021 for 31 regions in China. Data for all indicators comes from the China Statistical Yearbook (2012–2022), China Rural Statistical Yearbook (2012–2022), China Animal Husbandry and Veterinary Yearbook (2012–2022), and provincial Statistical Yearbook (2012–2022). The linear interpolation method was used to supplement missing values. To ensure the comparability of indicators, indicators related to prices have been conducted using an unchanged valence treatment, taking 2011 as the base period. Table 2 displays the variable descriptive statistics.

4 Results

4.1 Baseline regression results

To investigate the direct impact of the rural digital economy on AHCEI and AHPEI, we conducted panel regression models for baseline estimations. As shown in Table 3, when controlling for individual fixed effects only, the results indicate that the rural

Table 2 Statistics of explained variables, key explain variables and control variables (n = 341)

Variable type	Variable	Meaning	Mean	SD
Explained variables	*AHCEI*	Carbon intensity of animal husbandry	2.9	5.383
	AHPEI	Pollutant intensity of animal husbandry	0.44	0.693
Key explain variables	*Digital*	Rural digital economy development level	2.33	0.876
Control variables	*Gov*	Agricultural fiscal expenditure intensity	0.116	0.034
	Reg	Environmental regulation	0.640	0.721
	Feed	Feed production capacity	4.92	1.176
	Labor	Quantity of labor force	5.3	3.684
	Edu	Educational level	2.051	0.109
	Income	Income level of rural residents	0.406	0.133
	Lngdp	Regional economy development level	12.06	1.389
	Scre	Scientific research investment	1.15	1.298
	Stru	Animal husbandry structure adjustment	2.3	5.492

Table 3 Effect of the rural digital economy on AHCEI and AHPEI

Variable	Individual fixed effect model		Two-way fixed effect model	
	AHCEI	AHPEI	AHCEI	AHPEI
Digital	−1.183***	−0.095*	−1.192*	−0.200**
	(0.351)	(0.048)	(0.529)	(0.072)
Gov	−2.707	−0.338	−1.579	−0.617
	(7.448)	(1.022)	(8.242)	(1.117)
Reg	0.222	0.057	0.117	0.021
	(0.669)	(0.092)	(0.705)	(0.096)
Labor	1.069*	0.134*	1.182**	0.128*
	(0.424)	(0.058)	(0.451)	(0.061)
Feed	−4.373***	−0.264**	−4.573***	−0.322***
	(0.630)	(0.086)	(0.678)	(0.092)
Edu	−17.344***	0.544	−17.344***	0.472
	(3.875)	(0.532)	(3.936)	(0.533)
Income	−6.754**	−1.027***	−7.657**	−0.931**
	(2.244)	(0.308)	(2.413)	(0.327)
Lngdp	−0.778*	−0.149***	−0.895	−0.086
	(0.310)	(0.043)	(0.523)	(0.071)
Scre	8.032	2.327**	6.575	5.008***
	(6.031)	(0.827)	(9.314)	(1.262)
Stru	−0.073*	0.001	−0.070*	0.002
	(0.032)	(0.004)	(0.033)	(0.004)
Regional fixed	YES	YES	YES	YES
Year fixed	NO	NO	YES	YES
N	341	341	341	341
R^2	0.367	0.143	0.376	0.177

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

digital economy has a significant negative impact on both AHCEI and AHPEI. After adding year-fixed variables, the coefficients of the rural digital economy remain significantly negative. The results indicate that the rural digital economy significantly inhibits both carbon emission and pollution emission of animal husbandry; that is, the development of the rural digital economy can promote SCLCP.

Among the control variables, the coefficients of feed production and income level are significantly positive to promote SCLCP. The coefficients of government support and environmental regulation are not significant. The possible reason is that the current agricultural financial expenditure and environmental regulation mainly focus on constructing manure treatment facilities. Theoretically, improving the facility allocation rate will help reduce the pollutant emissions. However, facilities often face higher economic costs and professional quality requirements in the later stage, reducing the operational efficiency of livestock and poultry waste treatment facilities. An increase in the number of animal husbandry laborers will significantly increase the difficulty of SCLCP. The possible explanation is that the current animal husbandry laborers generally lack professional quality and experience, especially in applying pollution control and carbon emission reduction technology of animal husbandry, which will certainly not be conducive to the green transformation of animal husbandry.

4.2 Robustness test

We tested the robustness of baseline regression results in four ways: sample exclusion, eliminating extreme values, replacing core explanatory variables and considering endogeneity. The regression results are shown in Table 4. First, the study excluded the four remarkable central cities of Beijing, Tianjin, Shanghai and Chongqing. Since animal husbandry production in these cities accounts for a relatively low proportion of economic development, which may affect the accuracy of the estimation results when analyzing animal husbandry production activities. The regression results show that the negative impact of the rural digital economy on SCLCP remains significant and consistent with the baseline regression results. Second, to reduce the influence of outliers on the empirical results, the variables were pruned removing 1% and 99% quantiles. The mitigation effect of the rural digital economy development on SCLCP was still significant. Third, we replaced the core explained variable. Different empowerment methods may lead to differences in the measurement results of the rural digital economy development, which may affect the empirical results. Therefore, this study further used the entropy weight method to measure the rural digital economy development index, and the results still support the conclusion of benchmark regression.

Fourth, we considered endogeneity. Although the baseline regressions include fixed effects for year and region and several key control variables that affect AHCEI and AHPEI, potential endogenous issues may still arise due to unobservable variables and reverse causality. Considering that rural digital economy development depends on the popularity of the internet, which is closely tied to the early-stage planning and deployment of fiber-optic networks, this study used the spherical distance from provincial centroids to node cities in China's Eight Vertical and Eight Horizontal optical cable backbone network as an instrumental variable[52,53]. Regions designated as backbone network node cities were more likely to develop robust digital economies due to prioritized infrastructure investment. In addition, the distance metric is derived from historical geographic data, ensuring it has exogeneity. Since the distance variable does not change with time, this study compared the distance variable with the number of internet broadband access users nationwide to form an instrumental variable with time-varying effects. Table 5 presents the results of the Two-stage Least Squares. The first stage results indicate a significant influence of instrumental variables on rural digital economy, suggesting their explanatory power. Also, the Kleibergen-Paap rk Wald F statistic and Cragg-Donald Wald F statistic exceed the 10% critical value in the Stock-Yogo weak identification test, thereby rejecting any concerns regarding weak instrumental variables. In summary, considering endogeneity reveals that rural digital economy continues to exert a substantial mitigating effect on SCLCP.

4.3 Mechanism analysis

The above regression results reveal that rural digital economy

Table 4 Robustness test results

Variable	Sample exclusion		Truncated treatment		Replace explained variable	
	AHCEI	AHPEI	AHCEI	AHPEI	AHCEI	AHPEI
Digital	−2.226**	−0.307***	−0.337***	−0.239***	−6.414***	−0.374***
	(0.673)	(0.092)	(0.101)	(0.051)	(0.606)	(0.095)
Control variables	YES	YES	YES	YES	YES	YES
Regional fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
N	297	297	297	293	341	341
R^2	0.475	0.232	0.616	0.364	0.542	0.198

Notes: Values in parentheses are standard deviations; ** and *** indicate significance at 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

Table 5 Two-stage Least Squares regression results

Variable	First stage	Second stage	
	Digital	AHCEI	AHPEI
Digital		−4.817***	−0.594**
		(1.197)	(0.189)
IV	0.035***		
	(0.004)		
Control variables	YES	YES	YES
Regional fixed	YES	YES	YES
Year fixed	YES	YES	YES
Kleibergen-Paap rk LM	41.605{0.000}		
Kleibergen-Paap rk Wald F	68.500{16.38}		
Cragg-Donald Wald F	56.841{16.38}		
N	341	341	341
R^2	0.975	0.925	0.921

Notes: Values in parentheses are standard deviations; ** and *** indicate significance at 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

can jointly promote carbon emissions pollution reduction in animal husbandry. To further examine the internal mechanisms, we verified how the development of the rural digital economy to the reduction of carbon emissions and pollution in animal husbandry. As shown in Table 6, the development of the rural digital economy has a significantly positive impact on the green technology progress, resource allocation efficiency and production agglomeration. This indicates that rural digital economy development can reduce AHCEI and AHPEI through the effect of green technology progress, resource allocation efficiency improvement and production agglomeration. Therefore, our hypotheses 2, 3 and 4 are confirmed.

4.4 Heterogeneity

The rural digital economy, especially digital infrastructure and technologies, penetrates livestock production and has a

Table 6 Mechanisms test results

Variable	Green technology progress	Resource allocation efficiency	Production agglomeration
Digital	0.041*	0.088**	0.049*
	(0.018)	(0.027)	(0.024)
Cons	1.439***	0.730	−2.080***
	(0.422)	(0.651)	(0.577)
Regional fixed	YES	YES	YES
Year fixed	YES	YES	YES
Control variables	YES	YES	YES
N	341	341	341
R^2	0.653	0.257	0.582

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

stabilizing role, requiring government support. However, the level of agricultural support varies across local governments, which may lead to varying impacts of the rural digital economy on the effect of SCLCP. In addition, there are differences in the degree of marketization in different regions. The improvement of the degree of marketization may lower the threshold for advanced digital technologies to enter animal husbandry production so that the overall level of digital technology development is relatively backward, can fill the digital technology gap in a short period at low cost, and provide pollution reduction and carbon reduction in the rural digital economy. Therefore, we further tested if the effects of the rural digital economy on carbon emissions and pollution mitigation in animal husbandry differ under varying levels of government support and marketization.

Table 7 shows the heterogeneity analysis results of the impact of the rural digital economy on carbon emissions and pollution mitigation in animal husbandry. The interaction coefficients of the rural digital economy and government support are both significantly negative, which is consistent with the coefficient of baseline regression, indicating that government support can strengthen the effect of the rural digital economy on pollution reduction and carbon reduction of animal husbandry. Differently, the interaction coefficient of the rural digital economy and marketization level is significantly positive at the 1% level, indicating that marketization is not conducive for the effect of the rural digital economy on livestock carbon emissions and pollution mitigation. One possible explanation is that the purpose of marketization is to open up the circulation channels of factors through the market mechanism and improve the efficiency of resource allocation, which coincides with the mechanism of the rural digital economy to drive livestock carbon emissions and pollution reduction. This is inferred that the positive impact of marketization and rural digital economy on SCLCP has a specific substitution effect. Alternatively, implementing digital pollution reduction and carbon reduction requires a large amount of capital and technical investment, which typically relies on strong government support. Additionally, the increase in product demand accompanies the improvement of the marketization level. While blindly pursuing market income, production subjects may relax environmental control standards of livestock and poultry breeding, resulting in government supervision failure, which is not conducive to carbon emissions and pollution mitigation in animal husbandry.

To further examine whether the regulatory effects of government support and marketization vary across regions, this study classified provinces into three typological zones: agricultural zone, pastoral zone and agropastoral transitional zone. Table 8 presents the results of the regional heterogeneity analysis regarding the moderating effects of government support. The analysis revealed significant regional variations in

Table 7 Heterogeneity: the role of government support and marketization level

Variable	Government support		Marketization level	
	AHCEI	AHPEI	AHCEI	AHPEI
Digital	-1.400^{**}	-0.238^{***}	-3.104^{***}	-0.292^{***}
	(0.524)	(0.070)	(0.410)	(0.072)
Digital×Gov	-0.223^{**}	-0.041^{***}		
	(0.068)	(0.009)		
Digital×Mar			0.872^{***}	0.047^{***}
			(0.058)	(0.010)
Regional fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
N	341	341	341	341
R^2	0.398	0.232	0.670	0.264

Notes: Values in parentheses are standard deviations; ** and *** indicate significance at 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

Table 8 Heterogeneity I: the role of government support in different regions

Variable	Agricultural zone		Pastoral zone		Agropastoral transitional zone	
	AHCEI	AHPEI	AHCEI	AHPEI	AHCEI	AHPEI
Digital	−0.140**	−0.129**	−5.752	0.491	0.010	0.167
	(0.044)	(0.044)	(6.367)	(1.541)	(0.375)	(0.103)
Digital×*Gov*	−0.012*	−0.010	−0.771	−0.153	−0.123*	−0.062***
	(0.006)	(0.006)	(0.477)	(0.115)	(0.057)	(0.016)
Regional fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
N	231	231	44	44	66	66
R^2	0.752	0.313	0.912	0.505	0.892	0.903

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

policy effectiveness. The interaction terms demonstrate statistically significant negative coefficients in agricultural zone and agropastoral transitional zone, respectively, while no significant effects were observed in pastoral regions. These findings suggest that current government support mechanisms in agricultural and transitional provinces are more effectively in leveraging rural digital economy to achieve the dual objectives of carbon emissions and pollution mitigation in livestock production systems. Notably, the results underscore the imperative to optimize government interventions in pastoral provinces (e.g., Inner Mongolia, Qinghai, Xizang and Xinjiang), where existing policies exhibit suboptimal efficacy in harnessing digital transformation to advance sustainable development goals.

Table 9 presents the regional heterogeneity analysis of the moderating effects of marketization. The results show a statistically significant positive coefficient for the interaction term between rural digitization and marketization in the agricultural zone, indicating that higher marketization levels in these regions counteract the dual capacity of rural digitization to reduce AHCEI. Also, there is an asymmetric moderating

Table 9 Heterogeneity II: the role of marketization level in different regions

Variable	Agricultural zone		Pastoral zone		Agropastoral transitional zone	
	AHCEI	AHPEI	AHCEI	AHPEI	AHCEI	AHPEI
Digital	−0.185***	−0.141**	5.227	0.058	−0.698*	−0.116
	(0.050)	(0.050)	(2.875)	(1.732)	(0.293)	(0.089)
Digital×*Mar*	0.021*	0.010	2.214***	0.111	0.271**	0.036
	(0.008)	(0.008)	(0.290)	(0.175)	(0.083)	(0.025)
Regional fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
N	231	231	44	44	66	66
R^2	0.755	0.324	0.985	0.470	0.918	0.910

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

effect in the pastoral zone, where marketization exerts a significant negative moderating impact on AHCEI but shows no statistically discernible influence on AHPEI reduction. Then, we further identified divergent regulatory patterns in the agropastoral transitional zone, and found that marketization development appears to hinder the carbon reduction effect of the rural digital economy in the agropastoral transition zone, while its impact on pollution control is still negligible.

4.5 Spatial effect analysis

Before conducting out the spatial econometric model, it was necessary to determine whether the core variables have spatial autocorrelation. Therefore, the global Moran's I index of AHCEI and AHPEI was calculated using the geographical adjacency matrix. As shown in Table 10, the global Moran's I index of AHCEI and AHPEI in almost all years is significantly positive at the 1% level. This indicates a strong spatial autocorrelation in the distribution of AHCEI and AHPEI in Chinese provinces, i.e., geographical agglomeration. Therefore, using the spatial econometric model to examine the spatial spillover effect is essential.

Then, to determine the specific form of the spatial econometric model, this study conducted the LM lag, LM error and LR tests (Table 11). The results show that both LM and R-LM lag tests

Table 10 Global Moran's I of explained variables during 2011–2021

Year	AHCEI			AHPEI		
	Moran's I	*p*-value	*Z*-value	Moran's I	*p*-value	*Z*-value
2011	0.218	0.000	3.778	0.422	0.000	4.235
2012	0.221	0.000	3.822	0.443	0.000	4.458
2013	0.224	0.000	3.811	0.392	0.000	4.198
2014	0.229	0.000	3.826	0.412	0.000	4.338
2015	0.237	0.000	3.838	0.384	0.000	4.144
2016	0.343	0.000	4.291	0.256	0.002	3.049
2017	0.368	0.000	4.454	0.330	0.000	3.614
2018	0.385	0.000	4.556	0.268	0.005	2.837
2019	0.404	0.000	4.688	0.212	0.019	2.351
2020	0.438	0.000	4.830	0.140	0.069	1.818
2021	0.431	0.000	4.748	0.079	0.112	1.588

Note: The detailed descriptions of all abbreviated variables are provided in Table 2.

Table 11 Estimation results of spatial panel model tests

Test	AHCEI		AHPEI	
	Statistic	*p*-value	Statistic	*p*-value
LM-error	3.166	0.075	3.617	0.057
Robust-LM-error	0.238	0.626	14.029	0.000
LM-lag	20.338	0.000	24.076	0.000
Robust-LM-lag	17.410	0.000	34.488	0.000
LR-spatial error	28.490	0.002	83.720	0.000
LR-spatial lag	26.810	0.003	81.150	0.000

Note: The detailed descriptions of all abbreviated variables are provided in Table 2.

of AHCEI and AHPEI were significant at the level of 1%, and R-LM error tests of AHPEI were significant at the level of 1%, indicating the existence of spatial lag variables and spatial error terms. Also, the LR test statistics of AHCEI and AHPEI rejected the null hypothesis at the level of 1%, denoting that the SDM model is superior to the spatial lag and spatial error models. Therefore, a two-way fixed spatial Durbin model is adopted for the regression analysis.

Table 12 presents the spatial econometric regression results under the geographical adjacency matrix and economic geography matrix. These two matrices are used because livestock carbon emissions and pollution mitigation exhibit significant regional externalities, with potential joint control effects across geographically adjacent or economically similar regions. The geographic adjacency matrix effectively captured physical spillover paths, such as joint digital infrastructure development and environmental policy imitation. The economic-geographic matrix, which incorporated both economic development and distance, better reflected non-adjacent spillovers driven by the rural digital economy through factor mobility, technology diffusion and industrial collaboration. These results show that rural digital economy development has a significantly negative direct, indirect and total effect on livestock carbon intensity, indicating that local livestock carbon intensity is influenced not only by the local rural digital economy but also by its spatial interactions with surrounding regions. Notably, the rural digital economy significantly reduces livestock pollution intensity through direct effects, while the indirect effect is not statistically significant. A possible reason for this is that rural digital economic development is still in the initial stage. The extravasation speed, time lag, and threshold value of the rural digital economy may make its impact on the pollution intensity in neighboring areas insignificant. Therefore, our hypothesis 5 can be partially supported.

The results presented in Table 13 further reveals the differential moderating effects of government support and marketization level on the spatial spillover effects of the rural digital economy. The direct moderating effect of government support significantly amplifies the promotion of SCLCP by the rural digital economy, aligning with the regional policy effects revealed in Table 7. However, no measurable spatial spillover is observed from government support, indicating geographically bounded policy impacts. In contrast, marketization exhibits dualistic moderation. At the local level, marketization weakens the inhibitory effect of the rural digital economy on the SCLCP of local animal husbandry, which may be due to profit-driven crowding-out of environmental technologies. However, in the spatial dimension, it enhances the negative spillover effect of digital solutions on the AHCEI in neighboring regions. This can be attributed to the technology diffusion dividend brought by the cross-regional flow of market-oriented factors. This highlights the latent capacity of market mechanisms to transcend administrative fragmentation and foster regional emission governance coherence.

Table 12 Estimation results of spatial econometric model

Effect decomposition	AHCEI		AHPEI	
	$w(a)$	$w(e\text{–}g)$	$w(a)$	$w(e\text{–}g)$
Direct effect	-1.229^{*}	-1.257^{**}	-0.158^{*}	-0.201^{**}
	(0.503)	(0.477)	(0.068)	(0.070)
Indirect effect	-1.604^{*}	-3.114^{**}	−0.066	0.018
	(0.790)	(1.153)	(0.097)	(0.165)
Total effect	-2.833^{**}	-4.370^{***}	-0.224^{*}	−0.182
	(0.898)	(1.299)	(0.105)	(0.184)
Regional fixed	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
N	341	341	341	341

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

Table 13 Heterogeneity analysis of spatial effects

Effect decomposition	AHCEI			AHPEI		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Digital	-1.580^{**}	-1.772^{*}	-3.352^{***}	-0.214^{***}	0.013	-0.201
	(0.500)	(0.809)	(0.862)	(0.065)	(0.100)	(0.104)
Digital×Gov	-0.286^{***}	−0.054	-0.340^{**}	-0.052^{***}	0.077^{***}	0.025
	(0.061)	(0.129)	(0.129)	(0.008)	(0.016)	(0.016)
Digital	-3.285^{***}	1.671^{**}	-1.615^{**}	-0.277^{***}	0.107	−0.170
	(0.384)	(0.576)	(0.597)	(0.069)	(0.099)	(0.101)
Digital×Mar	0.940^{***}	-0.283^{***}	0.657^{***}	0.051^{***}	−0.028	0.023
	(0.055)	(0.083)	(0.077)	(0.010)	(0.015)	(0.013)
Regional fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
N	341	341	341	341	341	341

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. The detailed descriptions of all abbreviated variables are provided in Table 2.

4.6 Further analysis: exploring the potential negative impacts of market activities

Above, we mainly emphasize the positive role of rural digitization in reducing AHCEI and AHPEI, but lack research on its the relationship with animal husbandry consumption market. In fact, digitalization may stimulate the consumption of animal products, especially meat products, which in turn affects the supply of animal products and bringing higher carbon emissions and pollution emissions from animal husbandry. Therefore, we further examined the impact of the rural digital economy on urban per capita meat consumption (MC-UR) and rural per capita meat consumption (MC-RU), as well as its possible negative impact on the environment. The regression results are shown in Table 14. Columns 1 and 2

Table 14 Impact of the rural digital economy on local meat consumption

Variable	MC-UR	MC-RU	AHCEI	AHPEI	AHCEI	AHPEI
Digital	3.049^{*}	2.241^{*}	−0.262	-0.296^{**}	-1.509^{**}	-0.222^{**}
	(1.315)	(1.053)	(0.432)	(0.102)	(0.512)	(0.072)
MC-UR			-0.204^{***}	0.021^{***}		
			(0.025)	(0.006)		
MC-RU					0.141^{***}	0.010^{*}
					(0.028)	(0.004)
Regional fixed	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
N	217	341	217	217	341	341

Notes: Values in parentheses are standard deviations; *, ** and *** indicate significance at 5%, 1% and 0.1%, respectively. MC-UR, urban per capita meat consumption; MC-RU, rural per capita meat consumption. Since MC-UR was only announced in 2015, the number of observations is lower than the sample size. The detailed descriptions of other abbreviated variables are provided in Table 2.

show that the effects of rural digitization on MC-UR and MC-RU are significantly positive at the 5% level, indicating that rural digitization boosts the meat consumption of both rural and urban residents. Columns 3 to 6 further demonstrate the effects of MC-UR and MC-RU on AHCEI and AHPEI. The results reveal that rural dietary shifts toward increased meat intake exerted a dual intensification effect on both AHCEI and AHPEI, whereas increased urban meat consumption demonstrated a paradoxical divergence, significantly reducing AHCEI while elevating AHPEI. Overall, the negative environmental impact of rising meat consumption is evident, which confirms that rural digital economy may indirectly intensify AHCEI and AHPEI by stimulating market demand. Therefore, governments should continue to prioritize mitigating the environmental pressures associated by rising meat consumption, accelerate the adoption of low-carbon technologies in animal husbandry and optimize the structure of livestock products to achieve increased production with reduced emissions.

5 Discussion

SCLCP is an essential pathway to achieve high-quality environmental governance and climate change alleviation. This study establishes a novel research framework under the rural digital economy paradigm to reconcile the dilemma between conservation and development in animal husbandry, incorporating multi-objective considerations of carbon reduction, pollution control and economic growth. Currently, research in the agricultural sector mainly focuses on pollution and carbon emissions as separate research objects, with most focus on crop production systems[54,55]. Inspired by the homologous nature of pollutants and carbon emissions, this study pioneered an integrated analysis of how rural digital economy affects both carbon emissions and pollution reduction in animal husbandry. Building from existing literature, we extended the environmental benefits of the rural digital economy and the synergistic control of carbon and pollution framework to the livestock sector, thereby enriching the knowledge system. Our findings demonstrate that rural digital economy development effectively promotes SCLCP governance in animal husbandry, aligning with analogous conclusions in industrial sectors[56], thereby highlighting rural digital economy's cross-sectoral potential in coordinated emission reduction. This study also addresses the research gap in livestock pollution governance and its underlying synergistic mechanisms. In addition, unlike previous studies that used macro level digital economy indices[36], we construct a rural digital economy development indicator system based on the rural scale, which better reflects the actual impact of rural digital economy on the environmental governance of animal husbandry.

On the basis of verifying the effectiveness of SCLCP, this study systematically examined the multidimensional mechanisms, regional heterogeneity and spatial spillover effects of the rural digital economy in promoting SCLCP. Compared to prior work[57], we revealed that the synergistic governance efficacy of the rural digital economy stems not only from technological innovation but also from systemic transformations in factor allocation logic and spatial production agglomeration patterns, thereby expanding the analytical depth of existing research. In addition, we investigated the differential impacts of the rural digital economy on livestock pollution-carbon reduction from dual institutional perspectives (government support vs. marketization) across regions. The dialectical relationship between policy intervention and market forces uncovered holds significant theoretical value. Key findings indicate that government support significantly enhances the SCLCP effects of the rural digital economy in agricultural zone and agropastoral transitional zone, whereas marketization exhibits inhibitory effects in agricultural zone. This partially validates the necessity of government action to correct market failures through fiscal instruments and regulation[58]. These results provide actionable insights for local governments in formulating rural digital economy investments and livestock emission reduction policies. Also, the findings hold potential relevance for other developing or emerging economies undergoing similar transitions in rural digitalization and livestock production. In places such as Brazil, India and South-east Asia, where small and medium-sized livestock farming is prevalent, managing environmental pollution remains a major challenge. These countries could benefit from China's experience by developing integrated digital platforms for cross-regional coordination and promoting the formation of joint prevention and control mechanism of livestock pollution in adjacent areas. Critically, tailored livestock governance policies must account for local governmental and market contexts to ensure effective implementation.

Nevertheless, this study had some limitations. First, due to limitations in data acquisition and emission coefficients, the indicators for evaluating AHCEI and AHPEI are only accurate at the provincial level and do not take into account other links besides production; future research can consider deriving the measurement of AHCEI and AHPEI to the county or international scale, which will lead to more accurate results, and increase the scope of application of the results of the study to other countries or regions with similar economic and social conditions. Second, in terms of measurement indicators for the rural digital economy, although the author has focused as much as possible on the rural level, there is still a lack of more granular analysis. Future research could consider starting with micro farmers or digital livestock enterprises that actually participate in the rural digital economy, and conducting more detailed assessments of livestock production and environmental impacts. Finally, based on the weak boundaries and high permeability of the rural digital economy, it is also crucial for future studies to examine the role of digitization in promoting cross-industry synergies between the livestock industry and other sectors in future studies.

6 Conclusions and policy implications

Based on panel data from 31 provinces in China from 2011 to 2021, this study aimed to examine the coordination between pollution reduction, carbon reduction and economic growth in animal husbandry. Principal component analysis was used to comprehensively assesses rural digital economy development. The two-way panel fixed effect model, intermediary effect model and spatial Durbin model were applied to determine the influence, mechanism and spatial spillover effect of the rural digital economy on SCLCP.

There were four key findings. (1) Rural digital economy development helps to realize the synergy between carbon emissions and pollution mitigation in the livestock sector, and this relationship is robust after robustness tests and endogeneity tests. (2) Internal mechanism tests revealed that rural digital economy development effectively promotes SCLCP through three linear mechanisms: green technology progress, improved resource allocation and production agglomeration. (3) Heterogeneity analysis showed that government support further enhances the impact of the rural digital economy on SCLCP, especially in agricultural zone and agropastoral transitional zone. However, the impact of regional marketization level is opposite, and this adverse effect mainly occurs in agricultural zone. (4) The spatial effect indicates that local rural digital economy can promote livestock carbon emissions reduction in neighboring areas, with marketization exerting a positive moderating effect, while government support does not. Also, the impact of the rural digital economy on livestock environment pollution is confined to local areas, with no significant spatial spillovers observed.

Based on the above conclusions, we provide the following policy implications.

All localities could seize the opportunities to develop the rural digital economy and accelerate the construction of digital villages. Farmers can be encouraged to adopt smart agricultural technology to promote the digital transformation and development of green animal husbandry. Additionally, the village collective may coordinate efforts to facilitate the construction of digital infrastructure, creating a favorable social environment and conditions for implementing pollution and carbon reduction projects. This would effectively stimulate new momentum for the green and low-carbon development of animal husbandry and enhance its digital empowerment capacity.

Institutional barriers to technological progress, resource allocation, and production agglomeration need to be removed in order to fully release the potential of the rural digital economy to support sustainable and low-carbon practices. Efforts could focus on breaking through core technology R&D and promoting the adoption of digital technology. In addition, it is necessary to deepen the market-based allocation of factors in livestock production to encourage the free flow and efficient distribution of capital and labor. The government could also rationally plan the scope of key livestock production zones, enhance the efficiency and accessibility of digital governance, and might encourage industrial agglomeration in animal husbandry.

The positive effect of policy support must be strengthened, while the negative impact of marketization may need to be mitigated. Within the bounds of fiscal capacity, governments could increase investment in rural digital infrastructure and digitized production. Policies ought to be adapted to local conditions, especially in vast, sparsely populated pastoral areas with low digital literacy. Key measures may include boosting dedicated funding, strengthening broadband infrastructure, and promoting appropriate technologies such as satellite internet and low-power wide-area networks. At the same time, multilevel and diversified digital skills training programs are essential to ensure that herders can effectively utilize digital tools. Moreover, a clear boundary needs to be maintained between government intervention and market mechanisms to avoid distortions caused by excessive state involvement. Strengthening market regulation and governance would help sustain momentum for attracting and cultivating high-quality resources.

Finally, the government could actively promote interprovincial communication and collaboration by establishing an integrated information platform for digital cross-regional management. Such a platform would harness the demonstration and diffusion effects of leading digital provinces. Enhancing inclusive digital finance in rural areas, promoting the cross-regional flow of digital financial resources, and leveraging cross-regional resource allocation can effectively contribute to the coordinated governance of carbon emissions and environmental pollution in the livestock sector.

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Compliance with ethics guidelines

Ruirui Du, Liuyang Yao, Yu Lai, and Minjuan Zhao declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

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