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Original Research

Digital Rural Construction and Carbon Emission Intensity of Animal Husbandry: Evidence from China

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Abstract

The booming digital economy is a new engine for sustainable agricultural development. However, there are few studies on the impact of digital rural construction on carbon emissions from animal husbandry, and this study utilized China's provincial panel data from 2011 to 2020 and employed fixed effect models and instrumental variable methods to investigate such effects. Results indicate that digital rural construction significantly inhibits carbon emission intensity in animal husbandry. Further, regional and livestock species heterogeneity exists in terms of how digital rural construction affects local animal husbandry's carbon emission intensity reduction process; beef cattle, live pigs, and animal husbandry in central regions are more likely to benefit from it. Lastly, promoting technological progress and optimizing agricultural structure are the key paths for digital rural construction to achieve carbon reduction. Therefore, the government needs to emphasize the role of digital rural construction in the green development of agriculture while developing the rural areas according to local conditions.

Keywords: digital rural construction, animal husbandry, carbon emission intensity, technological progress, agricultural structure

Introduction

China proposed a "*dual-carbon*" goal to be achieved within the next 30 years in 2020. The combined efforts of pollution management and carbon emission reduction are instrumental in fostering the shift towards a green economy [1]. In recent years, China's livestock and poultry breeding industry has developed rapidly [2]. It is necessary to explore various factors that affect the emission intensity of pollutants from animal husbandry and seek ways to reduce these emissions [3]. Enteric fermentation and unreasonable manure management

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during animal breeding have emitted enormous amounts of greenhouse gases and become a major source of carbon emissions in China [4, 5]. Theoretically, the realization of carbon emission reduction (CER) in animal husbandry requires the input of capital factors and the promotion of low-carbon breeding technologies [6]. Currently, China's agricultural division faces limited access to capital resources, which obstructs the adoption of green production technologies; consequently, meeting practical rudiments for carbon farming becomes challenging [7, 8]. Therefore, under the realistic background of satisfying residents' effective demand for livestock products and realizing the goal of CER, how to address the practical limitations and achieve the CER goals in animal husbandry is a pressing issue.

With the popularization and application of digital technologies such as the Internet, cloud computing, and artificial intelligence in rural areas [9]. The digital economy, leveraging data-based knowledge and information as a novel component, infiltrates every side of agricultural production; it enables precision farming, reducing environmental impact, and enhancing crop yields [10]. It has emerged as a crucial avenue for minimizing transaction costs, integrating economic resources, and enhancing factor allocation proficiency [11-13]. Digital rural construction (DRC) has become a new engine to boost the transformation of agricultural and rural development methods and growth momentum. The transfer of agricultural land aimed at scale operation has not substantially advanced the development of sustainable agriculture; it is imperative to identify methods to enhance the acquisition of farmland in order to reduce the use of chemical fertilizers [14]. In this context, DRC can not only reduce the cost of green farming technology, information asymmetry, etc., but also greatly alleviate the difficulties of livestock financing [15]. This may provide new ideas for realizing low-carbon development in the livestock sector [16]. Furthermore, the implementation of DRC has the potential to enhance traceability and quality control within the livestock industry, ensuring a more sustainable and transparent supply chain that aligns with the growing consumer demand for eco-friendly and ethically sourced products [17]. So, does the development of DEC drive the CER of animal husbandry? What is its mechanism of action? This paper attempts to provide a theoretical reference for further promoting DRC to empower green agriculture by discussing the impact of DRC on the carbon emission intensity (CEI) of animal husbandry.

According to available literature, Fan and Xu [18] pointed out that digital knowledge and information are the key production factors of the digital economy. Owing to its cost-effectiveness, high returns, and permeability, it facilitates the unified integration of digital technology and economic production [19]. This, in turn, optimizes resource allocation and accelerates the adoption of green production methods. Deng and Zhang [20] further found that the digital economy has broken the traditional environmental supervision model where property rights are difficult to clarify and supervision costs are high. Li et al. [21] emphasized that Internet promotion not only expands knowledge dissemination channels and accelerates the accumulation of knowledge and technological innovation but also fosters environmental awareness. Environmental information shared through digital media inspires the public to adopt a green concept of environmental fortification and supports government, enterprises, and individuals in their environmental conservation efforts. Yang et al. [22] and Huang et al. [23] asserted that with its advantages of low cost and convenience, digital inclusive finance has broadened the coverage and depth of use of finance, alleviated the misallocation of financial resources, and improved the green production of enterprises. Specific to the CER effect of the digital economy, Xie [24] believes that the development of the digital economy has a positive effect on the reduction of urban CEI. Some scholars also believe that the development of the digital economy may also increase CEI; Hao et al. [25] postulate that the digital economy can help alleviate consumer budget constraints and stimulate the consumption of bulk power-consuming commodities. In addition, Lin and Ma [26] believe that the income effect caused by the digital economy will lead to faster power consumption, thereby increasing carbon emissions. Li et al. [27] found that the relationship between the digital economy and carbon emissions is affected by urbanization rate and population density. When the two exceed a certain threshold, the inhibiting effect of the digital economy on carbon emissions turns to a promoting effect. Currently, there have been studies focusing on the impact of digital economic development on green production, environmental pollution, air quality, and surface pollution concluding that the digital economy provides an opportunity for environmental quality improvement [28-31].

However, after combing the existing research, it is found that there are two limitations. First, the existing literature has begun to discuss the impact and mechanism of digital economy development on green production and environmental improvement, but the literature on the relationship between DRC and agricultural and rural environments is relatively scarce. Second, research on whether the digital economy promotes CER is still controversial, and previous studies have ignored the limited role of the digital economy in the process of CER in different industries.

This paper mainly explores the following three aspects: First, in terms of research content, based on the background of the digital countryside and "dual carbon", this paper discusses the issue of the impact of DRC on CER of animal husbandry, which not only fills the research gap, but also answers how to achieve the dual goals of "economic growth of animal husbandry" and "carbon emission reduction of animal husbandry". Second, from the perspective of research, this paper not only discusses the internal mechanism from the technical and structural effects, but also the non-equilibrium, which is of great significance for proposing specific carbon emission reduction policies for animal husbandry. Thirdly, in terms of research methods, this paper uses the historical data of posts and telecommunications in 1984 as instrumental variables. In order to avoid the endogenous problems caused by missing variables, such as unattainable factors such as digital policies and provincial endowments, based on the panel data of 31 provinces (cities, districts) in China from 2011 to 2020, this paper adopts the fixed effect model to empirically analyze the impact of DRC on the CEI of animal husbandry and to provide some support for improving China's animal husbandry CER strategy.

Theoretical Analysis and Research Hypothesis

The Direct Impact of DRC on the CEI of Animal Husbandry

DRC can effectively alleviate information and credit constraints in low-carbon livestock and poultry farming. DRC has changed the supply mode of traditional agricultural low-carbon production technology promotion. Digital components leverage information sharing and knowledge updates to improve the efficiency of transferring agricultural production knowledge, thereby contributing to the expansion of environmentally approachable practices among farmers [26, 28]. Access to production information reduces the cost of information collection for farmers to acquire and apply green technologies, thereby effectively improving the end-processing capabilities of farmers and reducing carbon emissions from animal husbandry. On the other hand, DRC breaks the spatial constraints of credit supply and credit demand, reduces the transaction cost of farmers' credit acquisition, and provides credit support for farmers to update their manure treatment facilities, thus improving the quality of animal husbandry manure [7]. The efficiency of resource utilization reduces the carbon emissions of animal husbandry. At the same time, DRC has significantly increased the output value of animal husbandry. In the prenatal link, DRC will promote the digitalization of the market, improve market information on agricultural factors, increase the knowledge accumulation of farmers, and improve the efficiency of factor allocation. In the middle of production, DRC improves the level of agricultural management and production efficiency. In the post-production link, DRC will broaden the sales channels of agricultural products and help increase agricultural output value. Based on this, this paper proposes:

Hypothesis 1: DRC will reduce the CEI of animal husbandry.

The Indirect Impact of DRC on the CEI of Animal Husbandry

Relying on the compatibility, intensification, and extensibility of digital technology, DRC has promoted the rapid flow and scientific integration of innovative knowledge, which is conducive to breaking the boundaries of innovation and improving the marginal benefits of technological progress in the animal husbandry sector [18]. Consequently, cutting-edge production approaches including smart feeding, intelligent environmental control, robots' pig-raising, and automated livestock facilities, have emerged. Moreover, these advancements have fostered growth in animal husbandry enterprises and scientific research institutions, particularly concerning livestock and poultry breeds, feed ratios, and manure management systems. Technological progress has indirectly reduced the CEI of animal husbandry. In addition, DRC can participate in the production of agriculture, forestry, animal husbandry, and fishery by virtue of its high permeability, which improves the rational allocation of

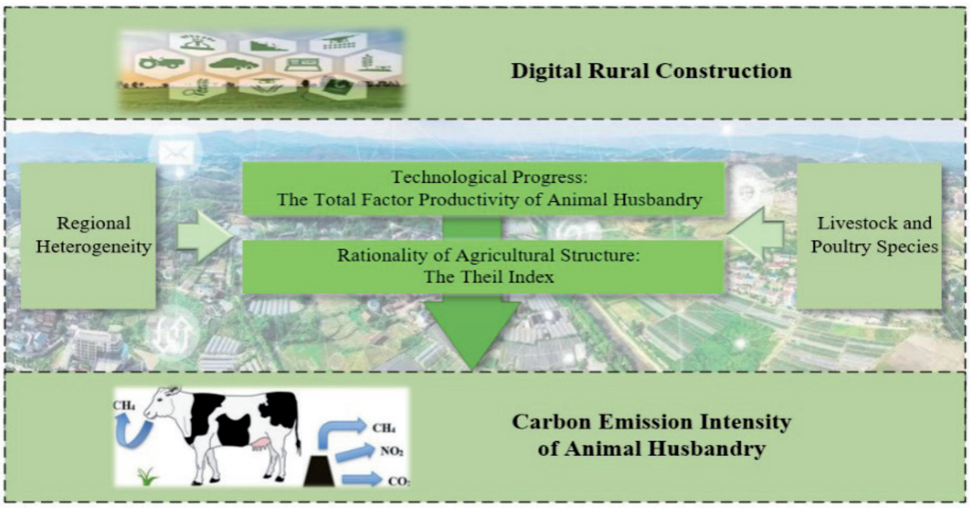

Fig. 1. The theoretical framework diagram.

its production factors. Thus, it successfully resolves the tension between the supply and demand of resources in both agriculture and animal husbandry, eventually impacting the agricultural production process [20]. The boundary of the combination of animal husbandry and animal husbandry reduces the marginal cost of the combination of agriculture and animal husbandry, promotes the coordinated development of agricultural structures, and reduces the CEI of animal husbandry. Based on this, this paper proposes:

Hypothesis 2: DRC can achieve the CER of animal husbandry by promoting technological progress and optimizing agricultural structure.

The theoretical framework diagram is shown in Fig. 1.

Materials and Methods

Data Sources

The data utilized in this study comprise panel data from 2011 to 2020, encompassing 31 provinces (cities, districts) across China. Information regarding the quantity of livestock and poultry slaughtered, stock levels, and their growth cycle is sourced from the "Compilation of National Agricultural Products Cost-benefit Data" and the "China Animal Husbandry Statistical Yearbook". Additionally, data on mobile phone penetration per 100 rural residents and rural broadband access are obtained from the "China Statistical Yearbook" and "China Rural Statistical Yearbook", respectively. The digital financial index employed originates from the esteemed "Peking University Digital Inclusive Finance Index". Population statistics and road mileage figures are extracted from the reliable source known as the "China Statistical Yearbook". Lastly, information pertaining to animal husbandry machinery's total power stems from the authoritative publication titled "China Agricultural Machinery Industry Yearbook". To address any missing values within our dataset, we applied an interpolation method. Furthermore, all output value data was standardized using the base year of 2011 for comparability purposes while simultaneously addressing any outliers present.

Core Variables

Explained Variable

Carbon Emissions Intensity of Animal Husbandry (CEI): It is not realistic to reduce the amount of breeding to achieve CER in animal husbandry. The key to emission reduction lies in the reduction of CEI [32]. The CEI of animal husbandry is the ratio of the total carbon emission to the output value of animal husbandry, that is, the carbon emission per unit of output value. The specific calculation Equation is as follows:

$$CEI = Car/OUT = (C_{CH_4} + C_{N_2O} = \sum N_i \times a_i \times 21 + \sum N_i \times \beta_i \times 310)/OUT \tag{1}$$

Among them, *OUT* is the output value of animal husbandry; *Car* is the carbon emissions of animal husbandry, the calculation method is based on the practice of Hu and Wang [33]; C_{CH4} and C_{N2O} are the greenhouse gas emissions of various types of livestock and poultry, respectively; N_i represents the annual average feeding amount of the *i* kind of livestock and poultry; a_i and β_i respectively indicate that the *i* animal produces C_{CH4} and C_{N2O} emission factors; *21* and *310* are respectively CH_4 and N_2O into CO_2 equivalent conversion factor.

Due to the different breeding cycles of various types of livestock and poultry, the average annual breeding quantity of livestock and poultry needs to be adjusted. Referring to the calculation method of Hu and Wang [33], when the slaughter rate is greater than 1, the annual average breeding number of livestock and poultry is divided by the slaughter amount by 365 and then multiplied by its life cycle. The livestock and poultry whose slaughter rate is greater than 1 are pigs and poultry, and the slaughter ratio of other livestock and poultry is less than 1. In addition, to avoid calculation errors caused by differences in livestock and poultry breeding systems and manure treatment systems in different regions, the emission factors of C_{CH4} and C_{N2O} adopted the "Provincial Wen's Emission Factor coefficients for the six major regions in the Gas Inventory Compilation Guidelines"[1].

Explanatory Variable

The level of digital rural construction (DRC): The connotation of DRC is to use digital information technology to promote the economic activities of agricultural production and rural economic development on the basis of constantly upgrading digital facilities. At present, there are extant works of literature on the measurement and calculation of DRC, but no unified approach. We can learn from Feng and Xu [34] and Zhao et al. [35] on the index of DRC. This article measures the level of DRC from two aspects: the level of rural informatization construction and digital inclusive finance. The number of households and rural delivery routes per 100 rural residents are three indicators. Digital finance has maintained a stable development trend in rural areas. The digital financial inclusion index adopts the China Digital Financial Inclusion Index jointly compiled by Peking University and Ant Financial

[1]http://www.cbcsd.org.cn/sjk/nengyuan/standard/home/20140113/download/shengjiwenshiqiti.pdf

Services Group [36]. Incorporating digital financial inclusion involves three key dimensions: coverage, depth of use, and degree of digitization. Standardize the data of the above six indicators and perform dimension reduction processing through the method of principal component analysis to obtain the comprehensive index of DRC.

Mechanism Variables

Technological Progress

Technological progress can improve the efficiency of resource allocation and is an important driving factor for improving the environment. In this paper, the total factor productivity of animal husbandry in each province (city, district) is taken as a proxy variable of technological progress, and the specific calculation method of total factor productivity is the Data Envelopment Analysis (DEA) model. Drawing on the processing method of Xu et al. [37], labor, intermediate consumption, and capital are selected as the input variables and the animal husbandry output value is the output variable. Specifically, the labor force of the livestock industry is expressed as the ratio of the output value of the livestock industry to the total output value of the primary industry multiplied by the number of people employed in the primary industry; the intermediate consumption is the value of the intermediate consumption of the livestock industry in each province; the capital is adjusted using the "perpetual inventory method", and then the amount of the capital investment in the livestock industry is calculated.

Rationality of Agricultural Structure

Reasonable agricultural structure optimizes the relationship between agriculture and animal husbandry in the region, thereby reducing carbon emissions from animal husbandry. Referring to the practice of Zeng et al. [38], the Theil index is used to measure the degree of rationalization of agricultural structure. As shown in Equation (2), where i is for each department; Y represents the total output value of agriculture, forestry, animal husbandry, and fishery; L means the intermediate consumption value of each industry; Ins indicates the rationality of the agricultural structure, and the larger the value, the more unreasonable the agricultural structure.

$$Ins=\sum_{i=1}^{n}\left[\frac{Y_i}{Y}Ln\left(\frac{Y_i}{L_i}\Big/\frac{Y}{L}\right)\right] \tag{2}$$

Instrumental Variable

To address the issue of endogeneity arising from mutual causality and omitted variables in the model, we utilized historical post and telecommunications data of each province (including cities and districts) in 1984 as the instrumental variable for the DRC index, drawing inspiration from Zhao et al. [35]. Firstly, the foundation of DRC is digital infrastructure, and digital infrastructure is the continuation of traditional communication technology. The past post and telecommunications infrastructure within each province (including cities and districts) has an impact on the ongoing construction of rural digital infrastructure. Hence, a correlation exists between the instrumental variable and the DRC index. Secondly, the frequency of traditional posts and telecommunications tools is gradually decreasing, and there is no direct connection with CEI of animal husbandry, which satisfies exclusivity.

Further, referring to the processing method of Nunn and Qian [39], the study incorporates a time-varying variable for panel data. Specifically, we construct this instrumental variable by taking the cross-product of two factors: the density of post and telecommunications services per 10,000 people in 1984 and the rural delivery route per 100 rural residents in the preceding year. Each province serves as an instrumental variable for the DRC index.

Control Variables

According to the existing research [40-42], we selected the following control variables, including economic development level (GDP), agricultural financial support (Finance), agricultural fixed asset investment (Invest), urbanization level (Urban), convenient transportation (Road), and total power of machinery (Mech).

Table 1 gives the definitions and descriptive statistics of the above variables.

Model Setting

This paper used the extended STIRPAT model [43], which allows other factors to be flexibly included in the process of analyzing environmental impact factors. It not only transforms the model into a linear form but also eliminates part of the influence of heteroscedasticity. The following benchmark model is constructed:

$$CEI_{it}=\beta_0+\beta_1 DRC_{it}+\beta X_{it}+r_i+u_i+\varepsilon_{it} \tag{3}$$

In Equation (3), CEI is the carbon emissions intensity of animal husbandry, X means control variables, r_i represents the individual fixed effect of the province (city, district), u_i represents the fixed effect of the control time, and ε_{it} is the random disturbance item, and β is the parameter to be estimated. To verify that DRC reduces the CEI of animal husbandry by promoting technological progress and optimizing agricultural structure, the following model is constructed:

$$Tech_{it}=\alpha_0+\alpha_1 DRC_{it}+\alpha X_{it}+r_i+u_i+\varepsilon_{it} \tag{4}$$

Table 1. Descriptive statistics for variables.

Type	Variables	Symbols	Explanation	Mean	Std. Dev
Explained variable	Carbon emissions intensity of animal husbandry	*CEI*	calculated	6.509	1.086
Explanatory variable	Digital rural construction	*DRC*	calculated	0.705	0.495
Mediating variables	Technological progress	*Tech*	calculated	1.027	0.108
	Rationality of agricultural structure	*Ins*	calculated	0.668	0.153
Control variables	Economic development level	*GDP*	Logarithm of GDP per capita	10.827	0.436
	Agricultural financial support	*Finance*	Logarithm of fiscal expenditure on agriculture, forestry and water	6.151	0.579
	Agricultural fixed asset investment	*Invest*	Logarithm of investment in fixed assets in agriculture, forestry, animal husbandry and fishery	6.008	1.276
	Urbanization level	*Urban*	Proportion of non-agricultural population	0.585	0.134
	Transportation convenience	*Road*	The ratio of highway mileage to administrative area	0.096	0.059
	Total power of machinery	*Mech*	Logarithm of total power of livestock breeding machinery	6.848	1.211
Instrumental variable	Historical post and telecommunications data	*IV*	Logarithm of historical data of post and telecommunications in each province (city, district) in 1984	5.903	1.082

$$Ins_{it}=Z_0+Z_1DRC_{it}+ZX_{it}+r_i+u_i+\varepsilon_{it} \quad (5)$$

In Equations (4) and (5), *Tech* is the total factor productivity of animal husbandry, and *Ins* is the rationality of agricultural structure, and α and Z is parameters to be estimated.

Results and Discussion

Benchmark Regression Results

Table 2 shows the baseline regression estimation results of the impact of DRC on animal husbandry carbon emissions. In models (1) and (2) and model (3) with control variables added, the estimated coefficient of the core explanatory variable DRC is significantly negative, which shows that DRC reduces the CEI of animal husbandry. Model (4) is the estimated result of the two-stage least squares method (2SLS). The statistics significantly rejected the null hypothesis of "insufficient identification of instrumental variables". At the same time, the Cragg-Donald Wald F statistic was 50.66, which was greater than the critical value at the 10% level of the Stock-Yogo test, indicating the instrumental variable Rationality of variable selection.

After considering endogeneity, the conclusion that DRC reduces the CEI of animal husbandry still holds true, and hypothesis 1 is verified. The main reasons are as follows: DRC provides farmers with convenient and unsecured loans, lowers the financing threshold for farmers to update low-carbon equipment, and expands the biological fermentation bed, aerobic fermentation, dry-wet separation machine, and other dung. The application of sewage resource utilization equipment has reduced the carbon emissions of animal husbandry. In addition, the construction of digital villages is inclusive, and while reducing information asymmetry and transaction costs in the industrial and service industries, it also provides an opportunity for the high-quality development of animal husbandry. For example, large-scale farmers with less farming experience can learn farming techniques through APP, which not only improves production efficiency, but also improves the efficiency of resource utilization of manure and realizes the transformation from extensive farming to green farming.

In relation to the control variables, both the economic development and financial support for agriculture did not demonstrate statistical significance. This lack of significance denotes that animal husbandry has not yet achieved a low-carbon economy, despite the observed economic growth and financial support for agriculture. The total power of animal husbandry machinery has not passed the test, which to some extent shows that animal husbandry is an extensive development model for increasing production. The impact of agricultural

Table 2. Benchmark model regression results.

Variable	(1) *OLS*	(2) *FE*	(3) *FE*	(4) *FE+IV*	
	CEI	*CEI*	*CEI*	*DRC*	*CEI*
DRC	-0.201***	-0.477***	-0.400***		-0.889**
	(0.020)	(0.139)	(0.114)		(0.343)
IV				0.021***	
				(0.003)	
GDP			-0.211*	0.505***	0.024
			(0.124)	(0.141)	(0.225)
Finance			0.023	0.002	0.018
			(0.050)	(0.038)	(0.053)
Invest			-0.054**	-0.008	-0.060**
			(0.022)	(0.025)	(0.030)
Urban			-0.224	-0.150	-0.274
			(0.183)	(0.132)	(0.221)
Road			-0.958***	0.024	-0.991***
			(0.261)	(0.149)	(0.284)
Mech			0.028	0.027	-0.034
			(0.042)	(0.060)	(0.062)
Cons	0.046	0.239**	0.258	-5.239***	-1.913
	(0.151)	(0.110)	(1.810)	(1.591)	(2.649)
Time	×	√	√	√	√
Region	×	√	√	√	√
R-squared	0.056	0.076	0.731	0.874	0.713
N	310	310	310	310	310

Note: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively, and robust standard errors are in parentheses.
Source: Author's own conception, using STATA software.

fixed asset investment and transportation convenience on animal husbandry carbon emissions is significantly negative. The main reason may be that the construction of agricultural and rural infrastructure is conducive to increasing the output value of animal husbandry, and it is also conducive to the resource utilization of livestock and poultry manure.

Robustness Test

In order to further ensure the reliability of the empirical estimation results, the more commonly used substitution variable method is used for robustness testing. Replace the explained variable. The per capita carbon emissions of animal husbandry are used to replace the explained variables, and then observe whether the conclusion after replacing the explained variables is still valid. Model (1) in Table 3 is the regression result of the model after controlling the time effect and individual fixed effect. The index coefficient of DRC is negative, significantly at the 1% level, which is consistent with the previous results. This indicates that the estimation results are robust.

On the other hand, replace the explanatory variables. Considering the long-term characteristics of DRC and the dynamic impact of DRC on the CEI of animal husbandry, this paper uses the DRC index with a lag of one period and two periods to replace the current data for robustness testing. To a certain extent, it avoids the endogeneity problem of bidirectional causality. The results of models (2) and (3) in Table 3 show that the coefficients of the DRC index in the first and second lag periods are significantly negative, in line with previous results. This re-verifies the conclusion that DRC can reduce the CEI of animal husbandry and also reflects the long-term inhibitory effect of DRC on the CEI of animal husbandry.

Table 3. Robustness test results.

Variable	Replace the explained variable	Replace the explanatory variable	
	(1)	(2)	(3)
DRC	-0.271**		
	(0.122)		
L.DRC		-0.411***	
		(0.098)	
L2.DRC			-0.460***
			(0.085)
Control variables	√	√	√
Time	√	√	√
Region	√	√	√
R-squared	0.001	0.584	0.560
N	310	279	248

Note: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively, and robust standard errors are in parentheses.
Source: Author's own conception, using STATA software.

Heterogeneity Analysis

Regional Heterogeneity Analysis

There are huge differences in the level of digital economy and animal husbandry development in eastern, western, and central China. In this paper, the heterogeneity of eastern, central, and western regions was analyzed. The regression results of models (1)-(3) in Table 4 show that DRC has a significant negative impact on the CEI of animal husbandry in the eastern, central, and western regions. The largest impact is in the central region, followed by the eastern, while the west is the weakest. A possible explanation is that the construction level of digital villages in the eastern region is relatively high. Furthermore, the standardization and scale of animal husbandry have already reached a high level, and the progress in animal husbandry appears to be consistent. Accordingly, the CER effect of digital villages is also expected to remain stable. With the continuous promotion of digital technology in the rural areas of central China, its penetration function and empowerment effect have become more prominent, and the CEI of animal husbandry in the central area is the most significant. The western region is mostly a resource-rich pasture area, and the production methods of livestock and poultry are relatively traditional. The rural non-agricultural sector has a limited ability to absorb the dividends of the digital economy; hence, the promotion effect is weak.

Heterogeneity Analysis of Livestock and Poultry Species

Since the cumulative carbon emissions of dairy cows, beef cattle, sheep, and pigs are more than 95% all year round, the production methods of different livestock and poultry species are very different. This part will explore the differences in the impact of DRC on the CEI of dairy cattle, beef cattle, sheep, and pigs. According to the estimated results of models (4)-(7) in Table 4, it can be found that the impact coefficients of the DRC index on the CEI of beef cattle and pigs are all negative, all passing the significance test. This indicates that DRC has a marked effect on the CER of beef cattle and pigs, and the size of the impact is different, with the strongest inhibitory effect on the CEI of pigs, followed by beef cattle. The regression coefficient of the DRC index on the CEI of dairy cows and mutton sheep is significantly positive.

The possible explanations are as follows: First, with the upgrading of the food consumption structure of Chinese residents and the further growth of the demand for dairy products, most of the dairy farms are expanding, but the concept, technology, and capital of farmers for green production are obviously lagging behind the scale expansion and production growth, and the production of mutton sheep is based on extensive grazing. DRC has led to a rapid increase in the production of dairy cows and mutton sheep, which has increased carbon emissions [44]. Second, the development stage of beef cattle and pig breeding is large-scale, standardized, and green development. DRC can solve the information constraints and credit constraints faced by farmers [45]. So, the development of DRC has a significant effect on the CER of beef cattle and pigs.

Table 4. Estimation results of heterogeneity analysis.

Variable	East	Central	West	Cow	Beef	Sheep	Pig
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DRC	-0.381**	-0.936***	-0.292*	0.381*	-0.166*	0.245**	-0.284**
	(0.156)	(0.255)	(0.148)	(0.208)	(0.097)	(0.111)	(0.114)
Control variables	√	√	√	√	√	√	√
Time	√	√	√	√	√	√	√
Region	√	√	√	√	√	√	√
R-squared	0.099	0.747	0.754	0.055	0.147	0.371	0.012
N	110	90	110	310	310	310	310

Note: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively, and robust standard errors are in parentheses.
Source: Author's own conception, using STATA software.

Table 5. Estimated results of mechanism test.

Variable	Technological progress		Rationality of agricultural structure	
	(1)	(2)	(3)	(4)
DRC	0.145***	0.143***	-0.350**	-0.348*
	(0.051)	(0.056)	(0.139)	(0.206)
Control variables	×	√	×	√
Time	√	√	√	√
Region	√	√	√	√
R-squared	0.331	0.133	0.006	0.103
N	279	279	310	310

Note: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively, and robust standard errors are in parentheses.
Source: Author's own conception, using STATA software.

Impact Mechanism Test

From the Perspective of Technological Progress

The regression results of model (1) and model (2) with control variables in Table 5 show that the DRC index coefficient is positive and significant at the 1% statistical level, indicating that DRC has promoted the technological progress of animal husbandry, and hypothesis 2 can be partially verified.

The possible explanation is that DRC has significantly improved the availability of resources in various agricultural sectors and promoted the increase in the frequency of innovation and the extension and diffusion of technological innovation. With the wide application of big data and artificial intelligence, animal husbandry has derived a new production model. For example, some leading pig-breeding enterprises are entering the era of intelligence. By implementing information technology and utilizing smart breeding platforms, they have facilitated the intelligent upgrade of equipment within pig houses. This includes improvements to ventilation temperature control, air filtration, and environmental monitoring. As a result, pigs now profit from a cleaner and more conducive growth environment. In addition, digital equipment such as electronic identification, precise feeding, and livestock and poultry manure treatment are used to accurately monitor the number of inputs and outputs of pig breeding, realize precise feeding of pigs, and promote continuous improvement of breeding efficiency, thereby reducing pig breeding carbon emissions [46].

From the Perspective of Agricultural Structure

The regression results of models (3)-(4) with control variables in Table 5 show that the coefficients of DRC are negative and have passed the significance test. This shows that the higher the level of DRC, the lower the deviation index of agricultural structure; that is, DRC is conducive to the optimization and adjustment of agricultural structure; hence, hypothesis 2 is verified.

The possible explanation is that DRC has deepened the degree of penetration among agriculture, forestry, animal husbandry, and fishery industries, enhanced the specialization and division of labor in the production of various agricultural departments, optimized the industrial chain links of various agricultural departments, and then promoted the rationalization of agricultural structure. The optimization of the internal structure of agriculture, forestry, animal husbandry, and fishery will change the carbon absorption and carbon emissions of the agricultural sector. The farming models such as grassland animal husbandry, a combination of forestry and animal husbandry, and a combination of planting and breeding can improve the carbon sequestration capacity of grassland, forest land, and agricultural land, thereby indirectly reducing CEI from animal husbandry [4].

Conclusions

Livestock and poultry production have problems with the high acquisition cost of green production technology and difficulty in financing the renewal of manure treatment equipment. This hinders the CER process of animal husbandry and also restricts the high-quality development of animal husbandry. Amidst the fast growth of the digital economy, advancing CER efforts in animal husbandry through the development of DRC serves as a vital avenue. Not only does it address the limitations of the animal husbandry production factor market, but it also aligns with the digital economy's imperative to modernize animal husbandry. This study empirically examines the impact and mechanisms of DRC on the carbon intensity of animal husbandry, using panel data from 31 provinces (including cities and districts) in China spanning the years 2011 to 2020. More so, the heterogeneity analysis shows that comparing the eastern and western regions, DRC has a greater effect on the CER of animal husbandry in the central region. Again, promoting technological progress and optimizing agricultural structure is an important way for DRC to reduce the CEI of animal husbandry.

In the context of promoting the construction of digital villages and facilitating the high-quality development of animal husbandry, the aforementioned research emphasizes two policy implications. Firstly, it is crucial to recognize the significance of DRC in reducing carbon emissions from animal husbandry. However, it should not solely rely on increased investment in information technology. It is imperative to promptly design and gradually implement a set of feasible guiding plans for digital infrastructure construction in rural areas. Secondly, measures need to be tailored to local conditions while harnessing the potential role of DRC in achieving CER within animal husbandry processes. Each region should make appropriate adjustments based on its specific circumstances, such as the internal structure of local animal husbandry and the level of agricultural development. This entails conducting targeted positioning analysis and developing an overall layout for functional supporting facilities accordingly. For instance, emphasis can be placed on technological progress and optimizing agricultural structure to facilitate ruminant CER; similarly, attention can be directed towards cleaner production methods and upgrading manure treatment techniques to promote CER in pig farming.

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Conflict of Interests

The authors declare no conflicts of interest.

Author Contributions

Conceptualization, X.B., Y.J., S.Q., J.L., and R.Y.; methodology, X.B., Y.J., Y.Z., J.S.; writing—original draft and editing, X.B., S.Q., Y.J., and J.S. All the authors were committed to improving this paper and are responsible for the viewpoints mentioned in this work.

Data Availability

Data can be requested from the corresponding author.

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