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Assessing the impact of China's National Big Data Comprehensive Pilot Zone policy on agricultural carbon emissions

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Abstract: The global focus on the relationship between digitisation and agricultural carbon emissions remains high. However, research on the systemic ramifications of comprehensive digital policy implementation remains limited. Against the backdrop of China's pursuit of carbon neutrality and carbon emission peaking targets, we employed the difference-in-differences method to investigate the impact of applying a digital policy on agricultural carbon emissions. Our findings indicated that the implementation of the National Big Data Comprehensive Pilot Zone policy could effectively mitigate agricultural carbon emissions, resulting in a sustained positive influence. The intermediary mechanism test results validated the beneficial effects of financial expenditures on science and technology, as well as the number of information practitioners. The regional heterogeneity analysis results revealed that the policy effect was obvious in the major grain-producing areas but not in the major grain-selling areas or production–marketing balance areas. Additionally, differences in policy effectiveness were observed across different crop types. This study not only offers valuable insights for agricultural carbon reduction in China but also provides robust case data and guidance for other developing countries worldwide in the formulation and execution of digital policies aimed at promoting agricultural carbon emission reduction.

Keywords: agricultural low-carbon development; digital economy; difference-in-differences method; policy effects

A favourable ecological environment serves as the foundation of human survival and development. Controlling greenhouse gas emissions has increasingly become an important strategic task for countries worldwide (Bai et al. 2019). China committed to a dual-carbon target (attaining peak CO_2 emissions by 2030 and achieving carbon neutrality by 2060) at the 75th United Nations General Assembly. For a long time, China has notably promoted green transformation of energy production and consumption and low-carbon development of industries (Yang et al. 2022).

However, agriculture in China has not yet completely changed from the high input–high output model. As reported by the United Nations Intergovernmental Panel on Climate Change, agriculture undoubtedly plays a significant role in the generation of greenhouse gas emissions (Bongaarts 2019). Rapid agricultural development is often accompanied by high consumption of resources and excessive carbon emissions (Aliyu et al. 2019). China's agricultural carbon emissions account for 17% of its total carbon emissions. The overuse of pesticides, fertilisers, and

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diesel is the key reason for such high emissions (Altieri 2017; He et al. 2018).

Research on the causes of agricultural carbon emissions has yielded fruitful results. Researchers have adopted the STIRPAT model to analyse and predict agricultural carbon emissions and have reported that the degree of mechanisation and structural conditions of agriculture are important influencing factors (Xiong et al. 2020). Survey data from eight African countries reveal that the agricultural innovation capacity also greatly influences agricultural carbon emissions (Pamuk et al. 2014). In addition, the effects of the scale of agricultural land operations (Koondhar et al. 2021), food prices (Pang et al. 2021), urbanisation (Asif and Almagul 2022), and advances in agricultural technology (Han et al. 2018) have been demonstrated.

The integration of big data with high-carbon emission areas is accelerating (Gohil et al. 2021; Lee et al. 2022). This has yielded many innovations in agricultural production, such as smart agriculture and precision agriculture. The application of these new technologies can increase the agricultural production efficiency and reduce resource consumption and environmental pollution levels (Huang et al. 2019). To achieve full mechanisation, precision and unmanned operations are needed in the four major fields of farming, planting, management and harvesting, while agricultural development should rely more on digisation to build smart farms. Existing experimental test results indicate that, compared with those of traditional mechanical operations, the digital farming efficiency is higher, and pesticide costs are reduced. Moreover, nearly half of the labour cost is saved, and farmers can achieve foreign exchange increase, emission reduction, consumption reduction, and recycling (Northrup et al. 2021). Overall, digital development can reduce agricultural carbon emissions by encouraging innovation and updating agricultural production technologies (Hou et al. 2024; Zhou 2024). Unfortunately, studies of the impact of the adoption of digital policies on agricultural carbon emissions are lacking.

On the basis of the above analysis, the literature can be enriched as follows: First, the impact of digital policy implementation on agricultural carbon emissions can be examined. We chose the policy of the first digital economy pilot zone in China in a quasi-natural experiment to examine the systemic impact of its implementation. Second, in terms of research methods, the application of the difference-in-differences (DID) method in policy effect assessment can prevent endogeneity problems. Moreover, fixed-effect estimation can resolve the problem of the bias due to missing variables. Third, in terms of the intermediary mechanism, we considered the financial expenditures on science and technology and the number of information practitioners. By examining the mechanisms of action for agricultural carbon emissions, we increased the understanding of the factors influencing agricultural carbon emissions.

Theoretical framework

China approved the establishment of two National Big Data Comprehensive Pilot Zone (NBDCPZ) batches in February and October 2016, covering regions including Beijing-Tianjin-Hebei, the Pearl River Delta, Shanghai, Henan Province, Chongqing Municipality, Shenyang Municipality, and the Inner Mongolia Autonomous Region. The various tasks of the NBDCPZ include promoting the application of big data, accelerating the management and sharing of data resources, and facilitating the establishment of big data industrial clusters. In the agricultural sector, the implementation of this policy contributes to agricultural emission reduction by promoting the collection, integration, analysis and application of agricultural data.

First, digitalisation can improve production and breeding methods in farmland systems, livestock systems and fishery systems (Braganza 2017; Acemoglu and Restrepo 2018). Digital technology can achieve visual management of the entire process of agricultural production, precise irrigation, precise fertiliser application, precise feeding, and intelligent temperature control management (Coble et al. 2018; Astill et al. 2020). At the subsequent stages, digitisation can enhance monitoring, risk warning, and accounting of farmland and pastureland (Lin et al. 2022). This could help reduce the emissions of pollutants such as particular matter 2.5 (PM) and CO_2 from all areas of agriculture.

Second, digital platforms can link hundreds of millions of participants and provide a digital platform for agriculture that meets different needs. In-depth integration of digital technologies such as cloud computing, big data and artificial intelligence with the agricultural industry can eliminate the data barriers between sectors, industries and levels and promote collaboration across the various links in the agricultural industry chain of production, processing, logistics and consumption to reduce emissions comprehensively (Li et al. 2021). Ultimately, we can establish a new agricul-

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tural industry with a green low-carbon and ecological cycle as a starting point.

Here, we proposed H_1 as follows: The implementation of the NBDCPZ policy can promote the reduction in agricultural carbon emissions.

With policy support, the governments of the pilot regions can increase their financial expenditures on science and technology to renew agriculture, which can positively impact low-carbon agricultural development (Li et al. 2022; Liu et al. 2022). On the one hand, the financial expenditures on science and technology provide financial support for agricultural technological innovation, promote the upgrading and transformation of agricultural technology, and ensure more environmentally friendly and efficient agricultural production (Doranova et al. 2010; Gallagher et al. 2011). For example, the development and application of agricultural technologies such as water-saving irrigation, drought relief and pest control should be promoted, and energy consumption and carbon emissions during agricultural production should be reduced. On the other hand, the financial expenditures on science and technology also facilitate the development of agricultural informatisation and intelligence, increase data analysis and decision-making capabilities in the agricultural production process, encourage optimisation of the agricultural production structure, and promote carbon emission reduction (Han et al. 2018).

A total of EUR 7.96 billion has been invested in information infrastructure construction in the pilot zones, and the level of information infrastructure development has steadily increased. The number of information practitioners has also increased substantially. Practitioners exhibit notable digital technology and data analysis capabilities, and they can provide more accurate and scientific services for agricultural production. Specifically, an increase in the number of information practitioners can reduce agricultural carbon emissions as follows: On the one hand, information practitioners can promote the application of green agricultural technology among farmers through information platforms and smart devices and guide them to adopt environmentally friendly and low-carbon agricultural production methods to reduce carbon emissions (Lee et al. 2022). On the other hand, information practitioners can employ information technology to establish agricultural carbon emission monitoring systems, monitor carbon emissions in the agricultural production process in real time and provide a basis for the formulation of targeted emission reduction strategies (Astill et al. 2020). Through digitisation and information services, farmers can more easily connect to the large market and better understand the specific needs of the market for green agricultural products. This can not only reduce the waste of agricultural resources but also encourage farmers to reduce the use of chemicals such as pesticides (Amiri-Zarandi et al. 2022).

Accordingly, we proposed H_2 as follows: Financial expenditures on science and technology and the number of information practitioners are intermediary factors influencing policy implementation.

In 2001, to adapt to changes in the grain production and distribution pattern, China divided all provinces into three categories, namely, major grain-producing areas, major grain-selling areas and production–marketing balance areas, so that advantageous grain production areas can consistently exert their geographical resource advantages and ensure the gradual increase in the grain production capacity. This division could influence policy effectiveness.

The natural landscapes in northern and southern China exhibit notable contrasts. North China experiences a dry climate, with relatively low precipitation in most areas and a relative lack of surface water resources. South China, however, exhibits a humid climate with abundant rainfall and relatively abundant water resources. These differences are also reflected in agricultural production. Farmers in North China face drought and water scarcity when growing crops and require crop varieties that are drought and cold resistant and highly resilient, whereas farmers in South China are more likely to grow moisture-tolerant crops such as rice and vegetables (Wang et al. 2020; Ma and Chen 2022; Zhu et al. 2022). In addition, the climate in South China is suitable for two or three crop seasons throughout the year, whereas in North China, there is mostly only one crop season with a short planting period.

Through the above analyses, we proposed H_3 as follows: The impacts of NBDCPZ policy implementation exhibit heterogeneity.

MATERIAL AND METHODS

Econometric modelling

The DID method is increasingly favoured as a tool in policy effect assessments. The basic principle entails the estimation of the net effect of a given policy by comparing the differences between the experimental and control groups before and after policy implementation, as shown in Figure 1.

In this study, we considered the NBDCPZ policy in a quasi-natural experiment and examined the impact

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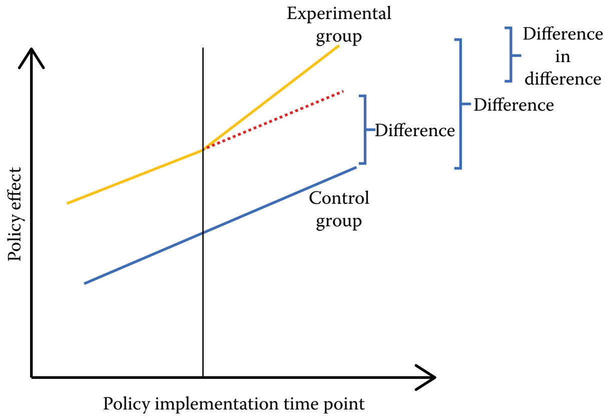

Figure 1. Schematic representation of the DID method

of policy implementation on agricultural carbon emissions via the DID method. We selected pilot provinces as samples. The specific model settings are as follows:

$$Y_{it} = \alpha + \beta DID_{it} + \delta X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where: Y_{it} – denotes the agricultural carbon emissions in province i during period t; DID_{it} – denotes the policy pilot shock; moreover, the pilot provinces constitute the experimental group, while the nonpilot provinces comprise the control group. In addition, α – constant term; β and δ – parameters to be estimated; X_{it} – time-varying control variable; μ_i – city fixed effect; γ_t – fixed effect in the corresponding year; ε_{it} – random error term.

Data sources

The analysis in this study is based on panel data from provinces, autonomous regions and cities in China from 2011–2021. The experimental group encompasses the provinces directly affected by NBDCPZ policy implementation. In contrast, the provinces in the control group are not affected by NBDCPZ policy implementation. All data were derived from the China Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Statistical Yearbook, and the statistical yearbooks of the provinces, autonomous regions and cities.

Description of variables

Explained variables. We used the carbon emission coefficient method of the United Nations Intergovernmental Panel on Climate Change (IPCC) to measure agricultural carbon emissions in each province, mainly considering the following six aspects: carbon emissions in the cultivation process mainly originate from the use of pesticides, fertilisers, agricultural films, machinery, irrigation and ploughing. The total agricultural carbon emissions (C) can be calculated via Equation (2).

$$\text{Carbon} = \sum \text{Carbon}_i = \sum E_i \times \delta_i \quad (2)$$

where: E_i – carbon emissions originating from source i; δ_i – carbon emission factor for source i; the carbon emission coefficients are listed in Table 1.

Explanatory variables. To better manifest the role of big data in promoting high-quality economic development, the State Council established two batches of a total of 10 provinces on the basis of the Outline of Action for Promoting the Development of Big Data in 2016, which provides suitable quasi-natural experimental conditions for this study. The core explanatory variable of this study is the policy shock (DID_{it}). Notably, when city i is selected as a pilot area in year t, DID_{it} is assigned a value of 1 in year t and the years thereafter. Otherwise, the value is 0. The regression coefficient of DID_{it} reflects the degree of change in agricultural carbon emissions before and after pilot policy implementation, which is the focus of this study.

Control variables. To increase the estimation efficiency of the regression model, the following variables were included: the plantation area (Zhao et al. 2010; Tian et al. 2015), crop disaster area (Davis et al. 2015), total agricultural output value (You and Wu 2014), number of large and medium-sized agricultural trac-

Table 1. Carbon emission coefficients

Carbon emission coefficient (CO_2)	Value	Unit	Reference
Fertilisers	0.8956	kg/kg	West and Marland (2002)
Pesticides	4.9341	kg/kg	West and Marland (2002)
Agricultural films	5.1800	kg/kg	Tian et al. (2011)
Diesel	0.5927	kg/kg	Wang and Zhang (2016)
Cultivated land	312.6000	kg/ha	Wu et al. (2007)
Irrigation	266.4800	kg/ha	West and Marland (2002)

Source: Generated by the authors

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Table 2. Descriptive statistics

Variables	N	Min.	Max.	Mean	SD
Plantation area (10 000 ha)	297	4.88	733.53	278.46	177.85
Crop disaster area (1 000 ha)	297	3.60	4223.7	836.06	756.70
Total agricultural output value (EUR $10 \cdot 10^8$)	297	6.30	833.21	262.19	166.90
Number of large and medium-sized agricultural tractors	297	2 900.00	1 060 600.00	193 610.04	206 225.84
Cereal production (tonnes)	297	62.95	7 104.39	2 184.97	1 770.63
Value added of the tertiary industry (EUR $10 \cdot 10^8$)	297	4.40	878.02	157.38	154.09
Financial expenditure on education (EUR $10 \cdot 10^7$)	297	9.88	481.88	112.07	75.53
Number of urban units employed in information transmission, software and information technology development services (10 000 persons)	297	0.20	80.60	9.65	10.74
Financial expenditure on science and technology (EUR $10 \cdot 10^7$)	297	0.43	148.34	15.35	21.47
Proportion of the value added of the tertiary industry	297	0.33	0.62	0.48	0.06
Fiscal expenditure on environmental protection (EUR $10 \cdot 10^7$)	297	16.05	747.44	147.20	100.29
Retail price index of food commodities	297	99.30	117.70	103.00	3.57
Agricultural carbon emissions	297	14.37	995.75	368.29	223.26

Source: Obtained by the author

tors (Dong et al. 2013), cereal production (Xiong et al. 2019), retail price index of food commodities, fiscal expenditure on environmental protection, and proportion of the value added by the tertiary industry.

Table 2 provides descriptive statistics of the chosen variables. Agricultural carbon emissions constitute the core variable, and in the observations, the minimum value is 14.37, and the maximum value is 995.75, indicating a large difference in agricultural carbon emissions. Moreover, the mean value is 368.29, and the standard deviation is 223.26. The standard deviation is large, indicating that the distribution of agricultural carbon emissions is relatively dispersed and highly volatile. This provides sufficient variability for DID analysis to help identify policy effects.

RESULTS

Basic regression

Table 3 provides the modelling results for the impact of the implementation of the NBDCPZ policy on the level of agricultural carbon emissions. The regression

Table 3. Benchmark regression results

Variables	Model 1	Model 2	Model 3	Model 4
	(1)	(2)	(3)	(4)
DID	−36.6197*** (−5.9300)	−14.8811* (−2.3700)	−18.1064*** (−3.3700)	−11.4993* (−2.1100)
Cons.	371.8688*** (227.2100)	362.7358*** (81.7200)	498.3870*** (8.3200)	311.7248** (2.9300)
R^2	0.0267	0.2468	0.3606	0.4196
Control	no	no	yes	yes
City FE	no	yes	no	yes
Year FE	no	yes	no	yes
Observations	297	297	297	297

*, **, ***$P < 0.05$; 0.01; 0.001, respectively; *T* statistics are provided in parentheses; *DID* – difference-in-differences; FE – fixed effects

Source: Obtained by the author

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results indicated that with every 1% increase in the degree of policy implementation, agricultural carbon emissions decreased by 11.4993%.

Robustness test

Flat trend detection. Before policy implementation, the treatment and control samples selected for empirical analysis should exhibit parallel trends. The test results are shown in Figure 2. Notably, the confidence intervals fluctuated around 0 before policy implementation. This result indicates that the parallel trend hypothesis is valid and meets the premise of the application of the DID method.

Individual placebo test. Considering the existence of 10 pilot provinces in benchmark regression, 10 provinces were selected herein as the pseudo-experimental group, and the other provinces constituted the pseudo-control group. To ensure more robust and reliable placebo test results, the above process was repeated 500 times. The results are shown in Figure 3, and most of the spurious regression coefficients reach a value of approximately 0 and obey a normal distribution. The regression coefficient (–11.4993) of the policy dummy variables in Column (4) of Table 3 of the basic regression model does not occur within the distribution range of the values of the false regression coefficient. Therefore, the base regression results pass the placebo test.

Time placebo test. Column (1) of Table 4 provides the time placebo test results. We predefined policy implementation 1 year before, and the results showed that policy implementation did not significantly promote the reduction in agricultural carbon emissions in the time counterfactual test. Notably, there was no systematic temporal trend difference between the experimental and control groups.

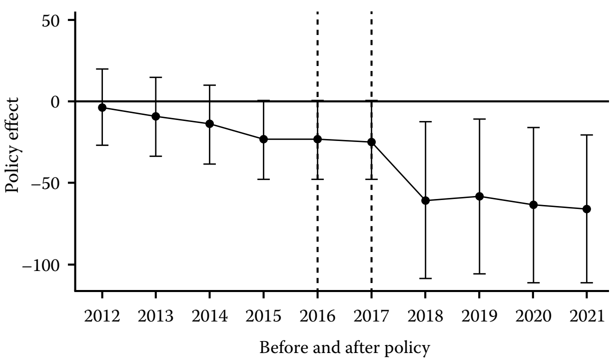

Figure 2. Dynamic parallel trends

Source: Generated by the author

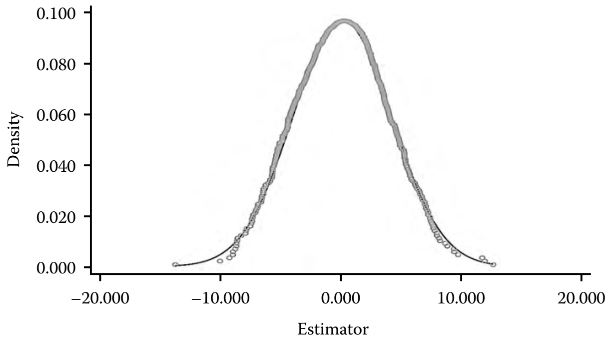

Figure 3. Placebo test

Source: Generated by the author

Exclusion of other major policies. Moreover, with respect to policy implementation, other policies were implemented in the experimental area, which may cause interference in the final results. Overall, the zone with the greatest direct impact on agricultural carbon emissions was the Ecological Civilisation Pilot Zone in 2016. The first provinces selected as national pilot zones include Fujian, Jiangxi and Guizhou Provinces. To assess the net effect of NBDCPZ policy implementation, we excluded the data of these provinces. The regression results are provided in Column (2) of Table 4, indicating significance.

Endogeneity test. We adopted the Propensity Score Matching (PSM) method. The PSM method was employed to establish more balanced treatment and con-

Table 4. Results of the exclusion of critical incident interference testing

Variables	Time placebo test	Exclude other policies	DID+PSM
	(1)	(2)	(3)
DID	–6.0079 (–0.9300)	–11.8699* (–2.0000)	–16.4420** (–2.6200)
Cons.	318.5622** (2.9700)	353.1525** (2.9000)	332.3708*** (10.7700)
R^2	0.4113	0.4015	0.4663
Control	yes	yes	yes
City FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	297	264	226

*, **, ***P < 0.05; 0.01; 0.001, respectively; T statistics are provided in parentheses, *DID* – difference-in-differences; PSM – Propensity Score Matching; FE – fixed effect

Source: Obtained by the author

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Table 5. Intermediary mechanism test

Variables	Agricultural carbon emissions	Financial expenditure on science and technology	Agricultural carbon emissions	Number of information practitioners	Agricultural carbon emissions
	(1)	(2)	(3)	(4)	(5)
DID	–11.4993* (–2.1100)	83.7082*** (5.3600)	–11.0941* (–2.1300)	5.1908*** (5.5800)	–10.7089* (–2.0400)
Financial expenditure on science and technology	–	–	–0.0628*** (–3.4100)	–	–
Number of information practitioners	–	–	–	–	–0.8959** (–2.7300)
R^2	0.4196	0.5668	–	0.4756	–
Control	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
Observations	297	297	297	297	297

*, **, ***P < 0.05; 0.01; 0.001, respectively; T statistics are provided in parentheses; *DID* – difference-in-differences; FE – fixed effect
Source: Generated by the author

trol groups, and DID analysis of the matched samples was then conducted to more accurately estimate the effect of policy implementation on reducing agricultural carbon emissions. The use of this method helps to eliminate potential selection bias, solve endogeneity problems, and increase the reliability of causal inference.

Through the comparison of the experimental calliper and proximity matching results, we determined that nuclear density matching can guarantee the closest match before and after matching, and the estimation results are more accurate. The empirical test data in Column (3) of Table 4 were obtained *via* PSM pairing, and the nuclear density matching technique was used to process the samples; then, the samples were retested. The results showed that the regression coefficients are all negative and statistically significant.

Table 6. Results for the major grain-producing areas and other provinces

Variables	Major grain-producing areas	Production marketing balance areas	Major grain-selling areas
	(1)	(3)	(2)
DID	–26.4684*** (–3.4000)	–21.8507 (–1.8900)	–6.0499 (–1.2900)
Constant	664.9345*** (3.5200)	215.1692 (1.6300)	180.7969 (1.4100)
R^2	0.6271	0.4262	0.9073
Control	yes	yes	yes
City FE	yes	yes	yes
Year FE	yes	yes	yes
Observations	143	110	44

*, **, ***P < 0.05; 0.01; 0.001, respectively; T statistics are provided in parentheses; *DID* – difference-in-differences; FE – fixed effect
Source: Generated by the author

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Table 7. Analysis of heterogeneity between North China and South China

Variables	Northern provinces	Southern provinces
	(1)	(2)
DID	−10.7521* (−2.5900)	−33.8951*** (−3.5200)
Cons.	259.7023* (2.3200)	323.9634*** (9.5900)
R^2	0.7663	0.4117
Control	yes	yes
City FE	yes	yes
Year FE	yes	yes
Observations	143	154

*, ***P < 0.05; 0.001, respectively; T statistics are provided in parentheses; FE – fixed effect

Source: Generated by the author

Intermediary mechanism results

We added the mediating variables in sequence in further regression analysis to explore whether these variables played a role. In the identification of intermediate effects in Column (2) of Table 5, the empirical results indicated that the policy helps increase the financial expenditure on science and technology. The results in Column (3) of Table 5 indicate that with policy implementation, the financial expenditure on science and technology increases, and agricultural carbon emissions decrease.

In the identification of intermediate effects in Column (4) of Table 5, the empirical results revealed that the regression coefficient of the NBDCPZ for the number of information practitioners is positive. The results in Column (5) of Table 5 showed that the influence coefficient of the increase in the number of information practitioners on agricultural carbon emissions is significantly negative, which confirms its mediating role.

Heterogeneity test results

Distinguishing between different types of grain production areas. The results provided in Table 6 indicate that inhibitory effects of policy implementation occur only in the main grain-producing areas but not in the main grain-selling areas or the production marketing balance areas.

Distinguishing between northern and southern provinces. The results in Table 7 reveal that the policy effectiveness of southern provinces in China is more significant than that of northern provinces.

DISCUSSION

On the basis of a quasi-natural experiment involving the NBDCPZ policy of China, we found that digital policy implementation can help reduce agricultural carbon emissions. This once again confirms the contribution of digital development to environmental sustainability (Lee et al. 2022; Yi et al. 2022; Hou et al. 2023; Zhou and Liu 2024). This study provides guidelines for China's sustainable development strategy and has important implications for the formulation and implementation of similar policies worldwide, especially in developing countries.

Specifically, we found that in the pilot areas, to better implement the policy, the government's financial expenditure on science, as an important part, increases accordingly. This occurs because to guide the development of the digital economy, science and technology have become key areas of financial expenditure and priority protection. The impact of fiscal expenditure on science on agricultural carbon emissions may be reflected in the following aspects: First, fiscal expenditure on science positively affects technological innovation. This provides technical conditions for precise agricultural planting and precise fertilisation, including the research and development and promotion of new varieties, disease and pest control, water-saving irrigation and other technologies (Zhu et al. 2023). These technologies help increase agricultural production efficiency and reduce the input of carbon sources such as fertilisers and pesticides, thus reducing agricultural carbon emissions (Li et al. 2022; Liu et al. 2022). Second, agricultural carbon emission monitoring and assessment capacities should be enhanced. Financial expenditures on science and technology can be used to support the research and development of agricultural carbon emission monitoring and assessment technology and increase the understanding and systematic management of agricultural carbon emissions (Zhao et al. 2023).

Moreover, we found that the construction of pilot zones promoted an increase in information practitioners. The possible reason is that the governments of pilot areas paid attention to the overall planning and opening of public data, created a big data innovation ecology, and strengthened the agglomeration

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and development of the big data industry (Qiu and Zhou 2021; Xu et al. 2022). This could attract many information practitioners and increase the demand for information practitioners.

The combined effect of these factors promoted an increase in the number of information practitioners in the pilot zones, which directly increases the level of information services in the region. An increase in information practitioners, especially those related to agricultural informatisation and digitalisation, can promote the digital transformation of agriculture, increase agricultural production efficiency, reduce the resource consumption per unit output, and thus help reduce agricultural carbon emissions (Henderson et al. 2020; Yang et al. 2023).

In terms of regional heterogeneity, this study revealed that the policy effect is pronounced in the major grain-producing regions, whereas it is less significant in both the major grain-selling areas and production marketing balance areas. This difference could stem from the fact that the major grain-producing regions are largely focused on grain cultivation, with relatively concentrated agricultural production. This concentration facilitates the implementation and oversight of big data technology, thereby rendering a greater policy effect. Moreover, as important areas of agricultural production, the main grain-producing areas may receive more attention and resource input from the government. This promotes the implementation of relevant policies in the major grain-producing areas, and the allocation of resources is more reasonable and adequate.

In addition, there are differences in the impact of policy implementation on agricultural carbon emissions between the northern and southern provinces. This may be due to the following factors:

i) Southern provinces experience a warm and humid climate with a long crop growth cycle and two or three crops per year as the main planting system features, whereas northern provinces exhibit a relatively cold and dry climate with a short crop growth cycle and mostly one crop per year (Wang et al. 2020; Ma and Chen 2022; Zhu et al. 2022). This results in notable crop growth, high photosynthesis, and high carbon uptake in the southern provinces but relatively low levels in the northern provinces.

ii) Mainly crops with high carbon absorption capacity, such as rice, are grown in the southern provinces, whereas mainly wheat, corn and other crops are grown in the northern provinces. The carbon sequestration capacity of different crops varies (Baumann et al. 2017).

iii) The culture in the southern provinces is more open and diverse, with a focus on innovation and change. This cultural background may render southern farmers more receptive to new policies and ideas.

Finally, there are still limitations in our study concerning the sample size, data quality, and temporal scope, which may influence the results. In future endeavours, we will more thoroughly analyse these differences by acquiring more granular data (including municipal-level data and extending the time frame).

CONCLUSION

Via the use of the DID method, we systematically explored the impact of the implementation of China's National Big Data Integrated Pilot Zone policy on agricultural carbon emissions for the first time, revealing the potential of big data policies for reducing agricultural carbon emissions. This finding provides a new perspective for digital policy-makers worldwide, highlighting the important role of big data technology in tackling climate change and sustainable development. The intermediary mechanism test results revealed that the financial expenditures on science and technology and the number of information practitioners played significant roles in reducing agricultural carbon emissions. Heterogeneity analysis was conducted to explain regional differences.

On the basis of the conclusions and analysis results, we believe that in the process of policy implementation, we should account for several problems to maximise policy effectiveness.

i) Policy-makers should encourage and support the broad application of big data technology in agriculture, especially in the monitoring, management and optimisation of agricultural carbon emissions.

ii) Governments should invest more in the research and development of agricultural technologies, especially those that help reduce carbon emissions. Through the establishment of special funds, tax incentives and other measures can encourage agricultural enterprises and scientific research institutions to conduct research and development and the application of low-carbon agricultural technologies.

iii) The government should strengthen the training and introduction of information practitioners to increase the level of agricultural informatisation. Through the establishment of scholarships, the creation of training opportunities and other measures to attract more talent for agricultural informatisation

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can provide technical support for reducing agricultural carbon emissions.

iv) When relevant policies are formulated, policymakers should fully consider the differences and particularities between regions. For different regions, differentiated policies should be formulated according to their actual conditions to ensure policy effectiveness and sustainability.

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