Original Research Article

Data elements empowerment and agricultural energy consumption: A quasi-natural experiments of national big data comprehensive pilot zone

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Abstract: As the core production factor in the digital economy era, data element is a powerful hand to promote the green development of agriculture. This paper regards the eight national big data comprehensive pilot zones (NBDCPZs) as a quasi-natural experiment, and investigate the effect of policies on agricultural energy consumption (AE) in NBDCPZs by using a differences-in-differences model. The results show that the policy of NBDCPZs has a significant effect on reducing AE, and this result passes the parallel trend test and a series of robustness tests. The moderating effect shows that the impact of the policy on AE in NBDCPZs is affected by the nonlinear moderation effect of optimum scale management, and the adjustment effect shows an inverted U-shaped characteristic. The heterogeneity analysis shows that the policy effect of NBDCPZs on AE is more significant in the central and western regions, the northwest of Hu Huanyong line with low population density. Accordingly, this paper provides evidence for reducing AE in NBDCPZs and offers policy recommendations for promoting high-quality development of agriculture.

Keywords: Agricultural energy consumption; National big data comprehensive pilot zone; Optimum scale management; Nonlinear moderating moderating effects

1. Introduction

Since the founding of the People’s Republic of China, to solve the problem of insufficient food supply, the growth model of China's agricultural economy has transitioned towards a pattern characterized by "high energy consumption, high pollution, and high output." Although the extensive agricultural development model has substantially increased China’s agricultural output, the challenges posed by global warming and the worsening agricultural production environment have further exacerbated the fragility of the agricultural ecosystem, posing a serious threat to food security. In recent years, China’s agricultural consumption demand has transitioned from a focus on quantity to an emphasis on quality[1]. Meanwhile, AE and pollution emissions have emerged as critical concerns within the framework of ecological civilization construction. The Central Document No. 1 of 2025 underscored the importance of fostering new high-quality agricultural productivity, promoting measures to reduce the use and enhance the efficiency of chemical fertilizers and pesticides, and elucidated the strategic direction for achieving low-carbon, environmentally friendly, and sustainable agricultural development. Under multiple constraints and significant pressure in production and operation, optimizing resource allocation, effectively reducing AE, and enhancing the resilience of agricultural ecosystem are among the critical challenges that need to be addressed in the work related to agriculture, rural areas, and farmers.

Since the onset of the new era, the integration and application of digital economy, 5G technology, and the Internet of Things have emerged as a critical driving force for promoting the green development of agriculture[2]. As a pivotal production factor and essential resource in the digital economy, data elements—characterized by low carbon emissions, strong diffusivity, and high environmental cleanliness—provide new avenues for promoting sustainable agricultural development[3], drawing considerable scholarly attention. On the one hand, some scholars have conducted research on the impact of data elements on the development of agriculture and rural areas. Gao et al.[4] analyzed the theoretical logic and mechanism of action of data elements in empowering high-quality agricultural development. Zhang et al.[5] hold that the development of the digital economy is highly beneficial to the improvement of the agricultural green total factor productivity. On the other hand, the extant literature on the influence of data elements on carbon emission reduction and energy efficiency has become increasingly abundant. Zhang and Xuan[6] employed static and dynamic panel models to demonstrate that intelligence is capable of reducing energy consumption and enhancing energy efficiency. Furthermore, with the elevation of the technological innovation level, the contribution of intelligence to improve energy efficiency becomes more significant. Ma et al.[7] delved into the direct and indirect influence effects of the digital economy on urban carbon emissions and unearthed that a spatial effect exists in the impact of the digital economy on carbon emissions. Additionally, some scholars have taken the first digital economy policy in China - the National Big Data Comprehensive Pilot Zones - as a quasi-natural experiment to investigate its economic benefits [8], environmental benefits[9], and innovation benefits[10]. Nevertheless, studies on the relationship between the policy of the NBDCPZs and AE are rarely reported.

Then, can the NBDCPZs effectively reduce AE? Do the effects of policy vary across different regions? What is the mechanism of its action? These are all the issues that this paper aims to solve. Therefore, this paper utilizes panel data from 30 provinces in China spanning from 2010 to 2021 to empirically investigate the impact of NBDCPZs on energy-saving performance in the agricultural sector. The main contributions of this paper are the followings: first, this paper uses a DID model to evaluate the agricultural energy-saving effect of NBDCPZs, expanding the theoretical framework of data elements enabling the enhancement of agricultural environmental performance. Secondly, we conduct a comprehensive analysis of the differential effects of the policy on agricultural energy consumption based on the perspectives of geographical location features and population density characteristics. Thirdly, we investigate the moderating effect of optimum scale management on the policy outcome, offering empirical evidence for the government to encourage rational agricultural land circulation.

2. Policy background, theoretical analysis and research hypotheses

2.1. Policy background

With the rapid development and widespread application of advanced information technologies such as the Internet of Things, cloud computing, and 5G, China has elevated the development and application of big data to a national strategy. In 2015, the Chinese government promulgated the "Action Outline for Promoting the Development of Big Data", and initiated the nation's first big data comprehensive experimental zone in Guizhou Province in September of the same year. In October of the subsequent year, the list of the second batch of NBDCPZs was disclosed. The establishment of the eight NBDCPZs have unlocked the potential value of data and jointly promoted the vigorous development of the big data industry.Currently, a number of scholars have undertaken significant research on NBDCPZs, yielding a wealth of substantial outcomes. Gao et al. [11] took NBDCPZs as exogenous policy shocks and empirically found that the policies have a promoting effect on the total factor productivity of enterprises. Sun et al. [12] conducted research by using the NBDCPZs as a quasi-natural experiment and found that big data policies can significantly enhance the development level of new quality productivity of enterprises. Liu et al. [13] discovered that although the policy effect of big data exhibits a certain degree of lag, its development can facilitate the low-carbon transformation of cities.

In summary, existing studies on NBDCPZs predominantly concentrate on enterprise total factor productivity [11], high-quality development [12], and green transformation and upgrading[13]. Nevertheless, the impact of NBDCPZs on AE remains underexplored, indicating a notable research gap in this area. During the crucial period when the new round of technological and industrial revolutions is advancing rapidly, investigating the influence of NBDCPZs on AE has significant practical value for promoting the construction of a strong agricultural country in China.

2.2. The impact of NBDCPZs on agricultural energy consumption

The establishment of NBDCPZs has continuously deepened the big data industry, and empowered the green and low-carbon development of the experimental zones. It can leverage the advantages of the digital economy and have an impact on the AE throughout the production process. Firstly, the application of digital technologies such as satellite remote sensing and big data analysis can be integrated into energy production and development[14], promoting energy transformation and revolution, enhancing agricultural production efficiency, and facilitating the development of precision agriculture [15]. It can also reduce the use of agricultural inputs such as fertilizers and pesticides while increasing their efficiency, lower the reliance on traditional fossil energy, optimize the energy consumption structure, improve agricultural green total factor productivity, and achieve the goal of conserving AE [16]. Secondly, the construction of digital information platforms can strengthen information sharing and collaboration among agricultural enterprises, minimize the phenomenon of information asymmetry, enhance the accuracy of farmers' production decisions [17], improve the matching degree of supply and demand for agricultural products, reduce ineffective supply, significantly enhance agricultural production efficiency and production benefits [18], and reduce energy consumption in the agricultural circulation end. Finally, the "Internet + Agriculture" model has overcome the limitations of the traditional agricultural operation and service framework, expanded the pathways for agricultural trade and distribution, and significantly contributed to enhancing the total factor productivity of energy [19]. Based on the above analysis, this paper proposes hypothesis H1:

H1: The establishment of NBDCPZs is capable of effectively reducing agricultural energy consumption.

2.3. The moderating effect of optimum scale management

In the context of the national food security strategy, promoting land transfer is an inevitable trend and also the core essence for realizing agricultural green development. Optimum scale management can improve agricultural production efficiency and decrease energy consumption per unit of output[20]. This is because when farmland is managed at an optimal scale, operators tend to adopt more advanced management practices, such as mechanized services, thereby influencing the utilization of agricultural energy in a more efficient manner. Firstly, optimum scale management can effectively alleviate land fragmentation, enabling operating entities to enhance agricultural production technologies[21], promoting the advancement of agricultural mechanization, improving the utilization of mechanical services and energy efficiency[22]. Secondly, optimum scale management can achieve standardization, efficiency and agglomeration in agricultural production[23], optimize resource allocation and improve the utilization efficiency of fossil energy. Finally, when operations reach a specific scale, the operating entity can conduct contiguous operations, precisely regulate the dosage and application intensity of chemical inputs, thereby reducing AE, and lowering agricultural carbon emissions. However, some studies have also indicated that, due to the inherent vulnerability of agriculture, optimum scale management may result in the simplification of crop diversity, reduce the resilience of agricultural ecosystems, and increase the risk of significant economic losses in the agricultural sector. Moreover, when the economic scale becomes excessively large, the complexity of agricultural production management rises significantly, potentially resulting in energy use inefficiencies [24]. Based on the above analysis, this paper proposes hypothesis H2:

H2: The impact of the policies for NBDCPZs on AE is nonlinearly moderated by optimum scale management, and this moderating effect exhibits an "inverted U-shaped" characteristic.

3. Models, variables and data

3.1. Model construction

3.1.1. Benchmark regression model

This article delineates the construction of NBDCPZs as a quasi-natural experiment and formulates a multi-period difference-in-differences model for empirical investigation.

$$AE_{it} = \alpha_0 + \alpha_1 \mathrm{DID}_{it} + \alpha_2 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

In Equation (1), AE_{it} represents agricultural energy consumption in province i in year t, DID_{it} is the core explanatory variable, representing the virtual variable of the NBDCPZs; X_{it} denotes a series of control variables, μ_i and γ_t denotes the province fixed effect and the year fixed effect, ε_{it} is the random disturbance term.

3.1.2. Moderating effect model

Considering the possible nonlinear moderating effect of optimum scale management in the policy impact effect, the quadratic term of optimum scale management is added to the moderating effect model:

$$\begin{aligned} AE_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 scale_{it} + \beta_3 DID_{it} \times scale_{it} + \beta_4 scale_{it}^2 + \\ \beta_5 DID_{it} \times scale_{it}^2 + \beta_6 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Among them, $scale_{it}$ denotes optimum scale management in province i in year t. The other variables are the same as above.

3.2. Variable description

3.2.1. Explained variable

The explained variable is agricultural energy consumption (AE). Drawing on existing relevant studies, this paper employs energy consumption per unit of agricultural output as the measurement indicator and applies deflation adjustment based on the constant prices of 2010[25].

3.2.2. Core explanatory variable

This paper selects national big data comprehensive pilot zones (DID) as the core explanatory variable. This variable is quantified by the interaction term between the regional dummy variable and the time dummy variable (Treat×Post), which serves as an indicator of whether the NBDCPZs policy has been implemented. That is, when a certain region is approved as a NBDCPZs, the value of Treat for that region is assigned as 1; otherwise, it is assigned as 0. As for the time dummy variable (Post), it is assigned a value of 1 for the year when the policy is implemented and subsequent years; otherwise, it is assigned a value of 0.

3.2.3. Moderating variable

This paper selects optimum scale management(scale) as the moderating variable. According to Zhu et al.[26], optimum scale management is represented by the ratio of the total sown area of crops to the number of agricultural employees in the primary industry.

3.2.4. Control variables

The control variables in this study consist of the following parts:(1) Agricultural planting structure (Str), measured by the proportion of the sown area of grain crops to the total sown area of all crops. (2) The level of fiscal support for agriculture (Gov), measured by the ratio of expenditure on agriculture, forestry and water affairs to the general public budget expenditure in each region. (3) The level of agricultural machinery (Mech), represented by the logarithm of the total power of agricultural machinery in each region. (4) The urban-rural income gap (IND), measured by the ratio of per capita disposable income of urban residents to that of rural residents[27]. (5) Human capital level (Hum), measured by the proportion of the number of students in higher education institutions to the total population in each region.

3.3. Data sources

This study' s sample covers 30 provincial-level administrative regions in China from 2010 to 2021. The data of agricultural energy consumption was calculated by the author. "China Statistical Yearbook" provides data on the level of fiscal support for agriculture, the urban-rural income gap and human capital level; The "China Rural Statistical Yearbook" supplies data on agricultural planting structure, the level of agricultural machinery and optimum scale management. Some missing data are supplemented by linear interpolation. The descriptive statistics of each variable are shown in **Table 1**.

Table 1. Descriptive statistics of variables.

Variable Name	Code	N	Mean	Sd	Min	Max
Agricultural energy consumption	AE	360	0.0787	0.0453	0.0000	0.2595
National big data comprehensive pilot zone	DID	360	0.1694	0.3757	0.0000	1.0000
Optimum scale management	scale	360	0.7592	0.3811	0.2090	2.9196
Agricultural planting structure	Str	360	0.6505	0.1498	0.3547	1.1618
The level of fiscal support for agriculture	Gov	360	0.1139	0.0329	0.0411	0.2038
The level of agricultural machinery	Mech	360	7.6774	1.1155	4.5433	9.4995
The urban-rural income gap	IND	360	2.6303	0.4410	1.8418	4.0735
Human capital level	Hum	360	0.0202	0.0056	0.0080	0.0425

4. Analysis of empirical results

4.1. Benchmark regression results

Table 2 presents the benchmark regression results both without and with the inclusion of control variables in a sequential manner. Regardless of the circumstances, the estimated coefficient of DID is significantly negative, indicating that the establishment of NBDCPZs can effectively reduce AE. Hypothesis H1 is verified.

Table 2. Benchmark regression results.

Variables	Reg (1)		Reg (2)	
DID	-0.0213***	0.0068	-0.0201***	0.0069
_cons	0.0823***	0.0019	-0.3588***	0.0671
Control variables	No		Yes	
Province fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
N	360		360	
r2	0.7521		0.7891	

Note: *, ** and *** indicate significance at the10%, 5% and 1% levels, respectively. Similarly hereinafter.

4.2. Parallel trend test

The precondition for employing the difference-in-differences approach is that the parallel trend test must be fulfilled. This paper refers to the research of Beck et al. [28] and employs the event study method to conduct a parallel trend test. The results are shown in **Figure 1**. The findings reveal that pre2 to pre4, there is no statistical significance, suggesting no notable discrepancies between the treatment and control groups prior to the establishment of the NBDCPZs. However, significant differences are observed post-implementation, satisfying the parallel trend assumption.

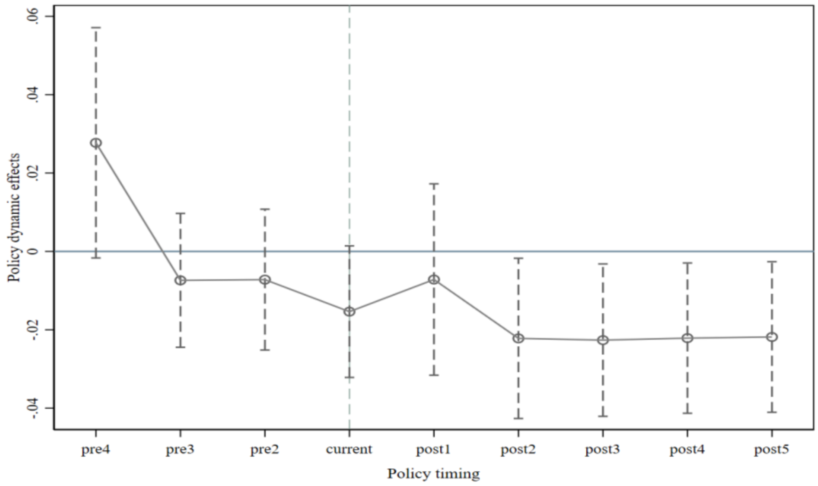

Figure 1. Parallel trend test.

4.3. Robustness test

4.3.1. Placebo test

To further confirm that the influence of NBDCPZs implementation on AE stems from the policy effects of the NBDCPZs, rather than being affected by other policies or random factors, this paper conducts a placebo test. Specifically, based on the original data, this paper conducts 1000 random samplings to obtain different treatment groups and control groups respectively, and acquires 1000 false estimation coefficients and corresponding P-values. Then, a kernel density distribution graph is generated for analysis and verification. The results of the placebo tests are shown in **Figure 2**. From this figure, the estimated coefficients of the placebo test are concentrated within the range from -0.01 to 0.01, and the majority of the P-values of the estimated coefficients are greater than 0.1 (indicated by the solid line in **Figure 2**), presenting a distribution approximately adhering to a normal distribution. However, the policy estimate value of -0.0201 in the article (indicated by the dashed line in **Figure 2**) shows a significant disparity from the estimation results of the random samples, thereby indicating that the impact of NBDCPZs on AE is unlikely to be disturbed by other policies or unobservable factors.

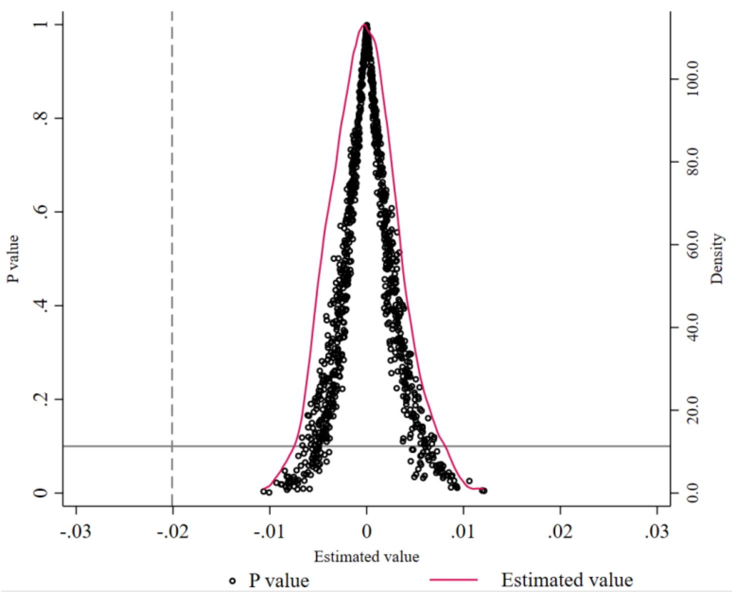

Figure 2. Placebo test results.

4.3.2. Other robustness tests

We further conducted robustness tests by employing techniques such as winsorizing the sample, introducing a one-period lag for the dependent variable, and refining the research sample. The results are shown in **Table 3**. First, to minimize the potential bias caused by outliers in the research results, this paper applies a 1% winsorization to both the dependent variable and all control variables at the upper and lower tails. The results are showed in **Table 3** column (1). DID remains significant at the 1% level with a negative coefficient, implying that the benchmark regression results are robust. Second, a one-period lag robustness test was performed on AE. The results are presented in column (2) of **Table 3**. The DID regression coefficient is significantly negative, suggesting that the implementation of the policy exhibits a lagged effect on reducing AE. Finally, this paper excludes the samples of Guizhou Province and uses the standard DID model for regression. The results in column (3) of **Table 3** show that after adjusting the research samples, the implementation of the policy of the NBDCPZs still significantly reduces AE. This also verifies the robustness of the benchmark results.

Table 3. Other robustness tests results.

Variables	(1) Winsorizing	(2) One-period lag	(3) Refine the research sample
DID	-0.0197***	-0.0193**	-0.0245***
	(0.0064)	(0.0077)	(0.0080)
_cons	-0.3654***	-0.3830***	-0.3453***
	(0.0658)	(0.0802)	(0.0682)
Control variables	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	360	330	348
r2	0.8127	0.7894	0.7950

4.4. Heterogeneity test

Influenced by historical culture, economic structure and climate, China's economic pattern shows obvious disparities. Therefore, this paper examines the diverse impacts of the implementation of NBDCPZs on AE by considering the geographical location The regression results are presented in **Table 4**. First, this paper divides the observation units into two major sections: the eastern region and the central and western regions. The results show in columns (1)-(2) that only in the central and western regions does the implementation of policies have a significant effect on reducing AE. A possible explanation is that the eastern region has a concentration of high-tech talents and a better foundation for networking and digitalization. Digital technology and agriculture have been well integrated, and the implementation of policies has no significant impact on energy consumption. However, in the central and western regions, digital infrastructure construction is relatively backward. Therefore, the implementation of policies has greatly enhanced the digitalization level of the central and western regions, accelerated the integration of data elements and traditional agriculture, promoted the improvement of agricultural production efficiency, and reduced AE. Additionally, considering that population density also affects the relationship between NBDCPZs and AE. Based on the Hu line as the dividing criterion, the sample data were divided into the southeast and northwest sides of the Hu line for regression. The results are shown in columns (3)-(4) of **Table 4**. It can be seen that compared with the southeast side of the Hu line, NBDCPZs have a more significant inhibitory effect on AE on the northwest side. This is because the northwest side of the Hu line has a relatively sparse population, which is conducive to achieving optimum scale management and reducing energy consumption caused by the repeated start-up of agricultural machinery. In contrast, the southeast side of the Hu line has a high population density and a high degree of land fragmentation, resulting in a relatively smaller marginal effect brought by policies[29].

Table 4. Heterogeneity test results.

Variables	(1)	(2)	(3)	(4)
	Eastern	**Central and western**	**Southeast side**	**Northwest side**
DID	0.0116	-0.0396***	-0.0144*	-0.0535**
	(0.0078)	(0.0129)	(0.0079)	(0.0245)
_cons	-0.3569**	-0.3717***	-0.2868**	-0.3104***
	(0.1628)	(0.0727)	(0.1182)	(0.0990)
Control variables	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	132	228	240	120
r2	0.8708	0.7767	0.7233	0.8981

4.5. Test of moderating effect

This paper conducts a further exploration of the moderating effect exerted by optimum scale management in policy effectiveness, with the results presented in **Table 5**. The coefficient of the interaction term between the policy dummy variable and optimum scale management (DID×scale) is significantly positive, while the coefficient of the interaction term between the policy dummy variable and the square of optimum scale management (DID×scale^2) is significantly negative. This indicates that there is a nonlinear moderating effect of optimum scale management on the relationship between the policy of NBDCPZs and AE, and it shows an "inverted U-shaped" variation characteristic. One possible explanation is that when farmland is operated on a moderate scale, the management entity adopts efficient new technologies for management, achieving an increase in production efficiency and thereby effectively reducing energy usage per unit of output, enhancing the effect of policy implementation. However, overly large-scale operation increases management complexity and raises operating costs. In such a situation, farmers are highly likely to pursue output by increasing energy usage and input of chemical production factors such as fertilizers and pesticides, leading to low or inefficient energy usage and weakening the effect of the policy. Thus, hypothesis H2 is verified.

Table 5. Test of moderating effect.

Variables	Reg (1)		Reg (2)	
DID	-0.0201***	0.0069	-0.0730***	0.0243
DID×scale			0.1422***	0.0493
DID×scale^2			-0.0767***	0.0182
_cons	-0.3588***	0.0671	-0.2701***	0.0624
Control variables	Yes		Yes	
Province fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
N	360		360	
r2	0.7891		0.8062	

5. Conclusions and recommendations

Using panel data from 30 provinces in China spanning 2010 to 2021, a multi-period difference-in-differences model is constructed for empirical analysis. The results showed that: first, the establishment of NBDCPZs can effectively reduce AE and has passed the parallel trend test. Moreover, after conducting robustness tests such as placebo tests, the conclusion still holds. Second, the test of the moderating effect reveals that optimum scale management has a nonlinear moderating effect on the policy implementation outcome. Specifically, moderate-scale operation can enhance the effectiveness of policies. Third, the heterogeneity analysis shows that the policy effect of NBDCPZs on AE is more significant in the central and western regions, the northwest of Hu line with low population density.

According to the above conclusions, the following suggestions are put forward: first, insist on implementing the policies of NBDCPZs, and leverage digital technologies to facilitate the transition of agricultural production patterns towards lower energy consumption. Second, accelerate land transfer to achieve optimum scale management, better exert the function of NBDCPZs in reducing AE. Third, have a distinct cognition of regional characteristics and make full use of regional comparative advantages to achieve green transformation.

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