scientific reports

OPEN

Impact of low carbon orientation on green finance in highly polluted areas based on STIRPAT spatial panel model

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In the context of the current global economic transformation, the integration of low-carbon economy and green finance has become a core issue in promoting sustainable development. This study focuses on the development of low-carbon finance in high pollution areas and explores its promoting effect on green finance. This study aims to analyze the impact of low-carbon orientation on green finance, clarify the intrinsic relationship between the two, and provide strategic recommendations for the development of low-carbon emission reduction finance in high pollution areas. To achieve the research objectives, this study used a random effects regression model and a spatial panel data model to conduct in-depth analysis of the carbon emission index in high pollution areas. The research results show that the Geary carbon emission C index in high pollution areas is significantly less than 0, indicating a negative correlation between carbon emissions and spatial distribution. The parameter values for financial scale and efficiency are 0.2031, 0.1125 and – 0.0089, 0.5365, respectively, while the parameter values for green finance are – 0.4154 and 0.0176. These data indicate that low-carbon policies have a significant promoting effect on green finance. The findings of this study have important practical significance for the development of green finance in high pollution areas. Given that green finance in the region is still in its infancy, research suggests further implementation of low-carbon emission reduction policies to promote the healthy growth of green finance and achieve dual benefits of economy and environment.

Keywords STIRPAT model, Spatial panel data, Low carbon orientation, Green finance

With global climate change and environmental problems becoming more and more serious, the development of a Low-Carbon (LC) economy has become a focal point for governments and society worldwide[1]. Highly polluted areas, as the primary sources of Carbon Emissions (CE), present a significant challenge in achieving a balance between economic development and environmental protection, a key issue in contemporary environmental conservation efforts[2]. In this context, the integration of an LC economy and Green Finance (GF) has emerged as a pivotal issue in advancing sustainable development. Global greenhouse gas emissions will reach a new record high in 2023, with high-carbon sectors such as energy and industry contributing more than 75 per cent of carbon emissions. At the same time, the theoretical framework for the integration of low-carbon economy and green finance is not yet perfect, and further research and construction of an interdisciplinary theoretical foundation are needed to better understand the interaction and synergistic effects between the two. And how to design and implement effective policies to promote the coordinated development of low-carbon economy and green finance is an urgent problem to be solved. Research also needs to analyze how to optimize financial mechanisms to better serve the development of low-carbon economy. There are differences in economic development level, industrial structure, energy efficiency, and environmental policy implementation among different regions. How to formulate differentiated low-carbon economy and green finance integration strategies based on these differences is also a current problem that needs to be solved. Highly polluted areas were chosen as the focus of the study because, as major sources of carbon emissions, these areas face the major challenge of achieving a balance between economic development and environmental protection. The carbon emission scenario in highly polluted areas is shown in Fig. 1.

This study, therefore, aims to delve into the impact of LC orientation on GF, particularly in highly polluted areas, and to explore how financial mechanisms can be leveraged to foster low-carbon emission reduction, thereby achieving dual benefits for the economy and the environment. GF, as an instrumental strategy for

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Fig. 1. Carbon emissions in highly polluted areas. (Source: self taken by the author Yunyan Yang).

fostering environmentally sustainable development through financial avenues, is garnering extensive attention[3]. It provides essential financial backing for LC technological innovation and clean energy investment, and also directs resource allocation through market dynamics to encourage an economic shift towards LC practices[4]. However, the existing body of research has predominantly concentrated on the economic growth implications of GF, often overlooking its unique role and potential impact on regional CE within highly polluted areas. This oversight represents a notable research gap, highlighting the need for a more comprehensive examination of the LC guiding role of GF in high-pollution areas and its potential for emission reduction. This study aims to fill the research gap mentioned above by systematically analyzing the relationship between low-carbon policies and green finance, and exploring their specific implementation effects in high pollution areas. The study will use spatial analysis tools and statistical methods to analyze in detail the carbon emission characteristics and green finance development levels in different regions. Using multiple model methods to evaluate the synergistic effect of low-carbon policies and green finance policies. Finally, a highly polluted area in northwest China was selected as a case study to analyze the implementation process and effects of specific policies.

Most existing research has focused on the impact of green finance on economic growth, while neglecting its unique role and potential impact on regional carbon emissions in high pollution areas. Although GF has great potential in promoting sustainable development, its application and efficacy in high pollution areas still need to be studied. In addition, the impact of LC policies in these regions and their effects on GF are areas worthy of further investigation. The current literature has recognized shortcomings in systematically analyzing the impact of LC policy direction on the development of GF in high pollution areas. Gao J et al. proposed an implementation path for green finance to assist in the low-carbon transformation of the economy, in order to achieve carbon peak and carbon neutrality goals, promote low-carbon economy and green finance market environment. The research results indicate that green finance contributes to the low-carbon transformation of the economy through industrial structure upgrading and technological innovation, and its intermediary role varies in different carbon emitting regions, providing a reference for addressing the difficulties in the low-carbon transformation of the economy[5]. Although Gao J et al.'s research can achieve differential effects on regional mediation, further exploration is still needed for the low-carbon economic impact in high pollution areas.Huang X et al. proposed a research method based on spatial Dubin model to address environmental pollution and reduce carbon emissions, promote green agriculture and low-carbon transformation, and empirically test the pollution reduction and carbon reduction effects of fiscal policies supporting agriculture. The research results indicate that agricultural carbon emissions and pollution are geographically dependent, and fiscal policies can reduce local emissions and pollution, with positive spillover effects and negative pollution reduction impacts and positive synergistic effects[6]. Although Huang X et al.'s research can analyze the impact of agricultural carbon emissions and green economy, further exploration is still needed for the development of green economy in high pollution areas.

Although current research can promote the development of low-carbon industries, further exploration is still needed for the low-carbon economy and green oriented development in high pollution areas. Low carbon orientation promotes the development of green finance through mechanisms such as policy guidance, market incentives, risk management, technological innovation, social cognition, synergies, and spatial spillover, and supports empirical analysis. In Xu B et al.'s study, the impact of the transformation of high energy consuming industrial enterprises on current green finance was explored and analyzed by examining the carbon dioxide emissions in different high pollution areas. The study analyzed the emission reduction effect of green finance through a mediation effect model, and the results showed that both green finance and carbon emissions can affect the energy consumption and emissions of urban industries in high pollution areas, and have an inverted U-shaped nonlinear effect[7]. However, research may be limited by geographical and temporal boundaries, data sources may be relatively single, exploration of industry specificity may not be in-depth enough, and may face endogeneity issues. Lin Z et al.'s study aims to explore the impact of green finance on China's low-carbon transformation in power generation and its intermediary mechanism. The entropy weight method is used to construct a green finance evaluation index system, and econometric models such as the generalized method of moments (GMM) and the difference in differences (DID) are used for empirical analysis. Research has found that the development of green finance has significantly reduced the proportion of coal-fired power generation in the total electricity generation, promoting the low-carbon transformation of China's power generation industry[8]. This study reveals the positive role of green finance in promoting low-carbon transformation in the power generation industry. However, current research on the impact of regional green finance orientation is still limited by time and geographical constraints, as well as possible endogeneity issues. In summary, the current research gaps mainly include the lack of in-depth analyses of the impact of the low-carbon economy in highly polluted areas, and the failure to fully explore the specific role of green finance mechanisms in these areas. Secondly, although the study has analysed the impact of agricultural carbon emissions on the green economy, there is insufficient in-depth research on the development of the green economy in highly polluted areas, especially in terms of the limitations of how to promote the green transformation of highly polluted areas through policy instruments.

To address this research gap, this study employs the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model and Spatial Panel Data (SPD) to conduct a thorough analysis of the effects of LC policy orientation on GF development in high-pollution areas. By examining the spatial correlation between CE and GF across various regions, the study elucidates the functional mechanism by which GF can stimulate the growth of an LC economy. The study's innovation lies in the construction of a tailored model for financial analysis concerning low-CE reduction in high-pollution areas, complemented by the utilization of the Lagrange Multiplier (LM) test to assess the fixed model, thereby enhancing the model's precision. The study uses the STIRPAT spatial panel model and random effects regression model to comprehensively analyse the impact of low carbon policies on green finance in highly polluted areas. The spatial dependence of carbon emissions is assessed by Geary's C index, data stability is verified using LLC and IPS tests, and regression analyses are carried out by combining fixed-effect and random-effect models to assess the long-term and short-term effects of policies. The results of the study will provide a scientific basis for the formulation of differentiated low-carbon policies and the optimisation of green financial development in highly polluted regions, and promote the coordinated development of regional economy and environment. Additionally, the study offers refined recommendations and developmental trajectories for GF in high-pollution areas, with the goal of establishing a more robust scientific foundation and theoretical framework to inform policy decisions and regional growth strategies. Moreover, this study delves into the application of GF in high-pollution areas and investigates how financial innovation and policy support can promote the broad adoption of low-carbon technologies, creating scenarios that include the utilization of clean energy, the promotion of low-carbon transportation, and the establishment of zero-carbon buildings and residences. These initiatives are designed to achieve cross-sectoral synergies and drive a comprehensive green transformation of the economic and social fabric. Through these analyses, the study can offer novel perspectives and strategies for the advancement of GF in high-pollution areas, contributing to the pursuit of an LC economy. The theoretical framework structure of the current research is shown in Fig. 2.

In Fig. 2, the study first integrates environmental economics, green finance theory, and sustainable development theory to construct the theoretical foundation for the research. Secondly, choose the STIRPAT model to analyze the impact of population, economy, and technological level on carbon emissions. Then define the variables in the study, such as carbon emission index, financial scale, financial efficiency, and green finance indicators, and collect relevant data from high pollution areas to provide data support for empirical analysis. Conduct in-depth analysis using random effects regression model and spatial panel data model. Finally, based on empirical results and theoretical perspectives, policy recommendations are proposed, such as implementing low-carbon emission reduction policies, providing tax incentives and financial incentives, etc.

The research findings will provide scientific basis for policy makers to develop more effective low-carbon policies and green finance strategies. By analyzing regional differences and policy synergies, resource allocation can be optimized and policy implementation effectiveness can be improved. In addition, the research results will also provide reference for financial institutions and enterprises to better plan their green transformation paths and achieve a win-win situation between the economy and the environment .The contributions of this study are as follows: Firstly, this study fills the gap in existing research on the synergistic effect of green finance and low-carbon policies in high pollution areas, breaks through the general analysis of the macro impact of green finance in traditional research, and provides a new perspective for understanding its differentiated role in specific regions. At the same time, the study explores how low-carbon policies can promote the development of green finance through spatial spillover effects and financial mechanism optimization, providing scientific basis and policy references for global efforts to address climate change and achieve sustainable development goals.

The innovation of this study is as follows: This study used the STIRPAT model and spatial panel data method, combined with the random effects regression model and spatial autoregression model, to construct a comprehensive analysis framework that can simultaneously consider the effects of time series and spatial dimensions, improving the accuracy and reliability of the model. In addition, the study combines environmental economics, green finance theory, and sustainable development theory to construct an interdisciplinary theoretical framework. It proposes a theoretical hypothesis that low-carbon policies promote the development of green finance through various mechanisms and verifies it through empirical analysis.

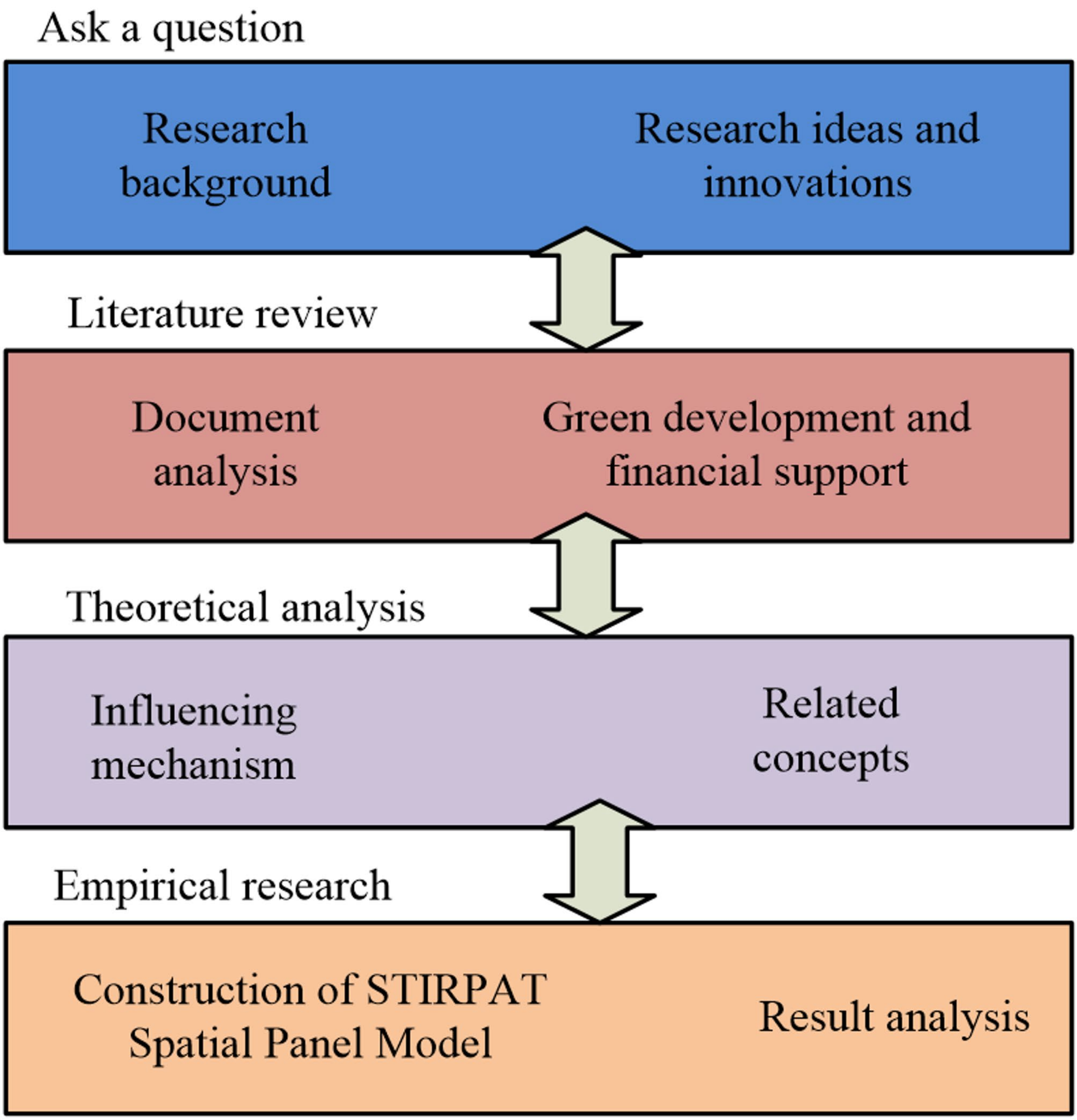

Fig. 2. Research theoretical framework.

Methods and materials
Theoretical analysis
Low carbon economy refers to pursuing a low emission, low pollution, and high-efficiency economic development model through LC development. The development of low-carbon economy is based on the theory of environmental economics, which holds that economic growth and environmental quality can go hand in hand. Through technological innovation and institutional change, it is possible to achieve low-carbon economic activities, reduce dependence on fossil fuels, and thus lower carbon emissions. "Low carbon" refers to reducing air pollution and CE to enhance the carrying capacity of the environment, ensuring that current pollutant emissions are within the acceptable range of the environment[9]. "Economy" refers to the innovation of energy-saving and emission reduction technologies while ensuring the growing of the national economy, reducing the consumption of fossil fuels, improving energy utilization efficiency, and enabling current economic development to meet "Low carbon" standards, achieving Sustainable Development (SD) of nature and economy[10]. The implementation GF can facilitate climate change response strategies and promote the efficient utilisation of resources[11].

GF refers to all financial activities that can promote SD of the ecological environment[12]. The provision of financial services by GF has the objective of directing the flow of funds towards environmentally friendly projects, the promotion of sustainable economic and social development, and the achievement of the financial industry's SD[13]. The development of green finance is closely related to environmental finance theory, which holds that financial markets and institutions play a key role in promoting environmental sustainability. Green finance helps achieve dual benefits of environmental goals and economic growth by directing funds towards environmental projects and green technologies. In addition, green finance also involves the theory of corporate social responsibility (CSR), emphasizing that while pursuing economic benefits, companies should also take responsibility for the environment and society. Furthermore, it has been demonstrated that GF can serve to diminish CE and facilitate the advancement of sustainable economic growing[14]. GF can also guide more social capital into the green and LC field through innovative institutional arrangements and market-oriented principles, providing diversified, specialized, and differentiated financial services.

SD mainly includes three interdependent dimensions: environment, economy, and society, emphasizing the coordinated development of the three aspects[15]. SD includes several basic principles: the principle of fairness emphasizes fairness for all people living in the same time period, fairness between people living in different time periods, and fairness in resource; The sustainability's principle requires that the economy growing and society should not exceed the maximum number of organisms that a given environment can sustain; The principle of commonality recognizes the necessity for global collaborative endeavors to attain SD objectives. SD needs to conform to the laws of nature, maintain the ecological environment, and achieve harmonious development between humans and nature.

Analysis of the impact mechanism of CE orientation and GF

The financial scale is measured by calculating the total assets or total loans of financial institutions in various regions. The data in the study are from the annual reports of the People's Bank of China or local branches[16]. Financial returns are measured by calculating the net profit or return on investment of financial institutions, with data sourced from publicly available financial statements or industry analysis reports[17]. Green finance is measured by evaluating the investment ratio of financial institutions in green projects or the quantity of green finance products. The data sources include green finance policy documents, sustainable development reports of financial institutions, or green finance databases[18]. In the process of financial development, there is a mechanism of mutual influence between finance and CE. In finance, there are three main components: financial efficiency, financial scale, and GF. The financial benefits and scale determine the output of financial products. But when the output of financial products increases, the CE quantity of the entire economic environment also increases accordingly. Expanding the financial scale meanwhile can lead to more financial benefits moving towards GF direction. Figure 3 illustrates the relationship between finance and CE.

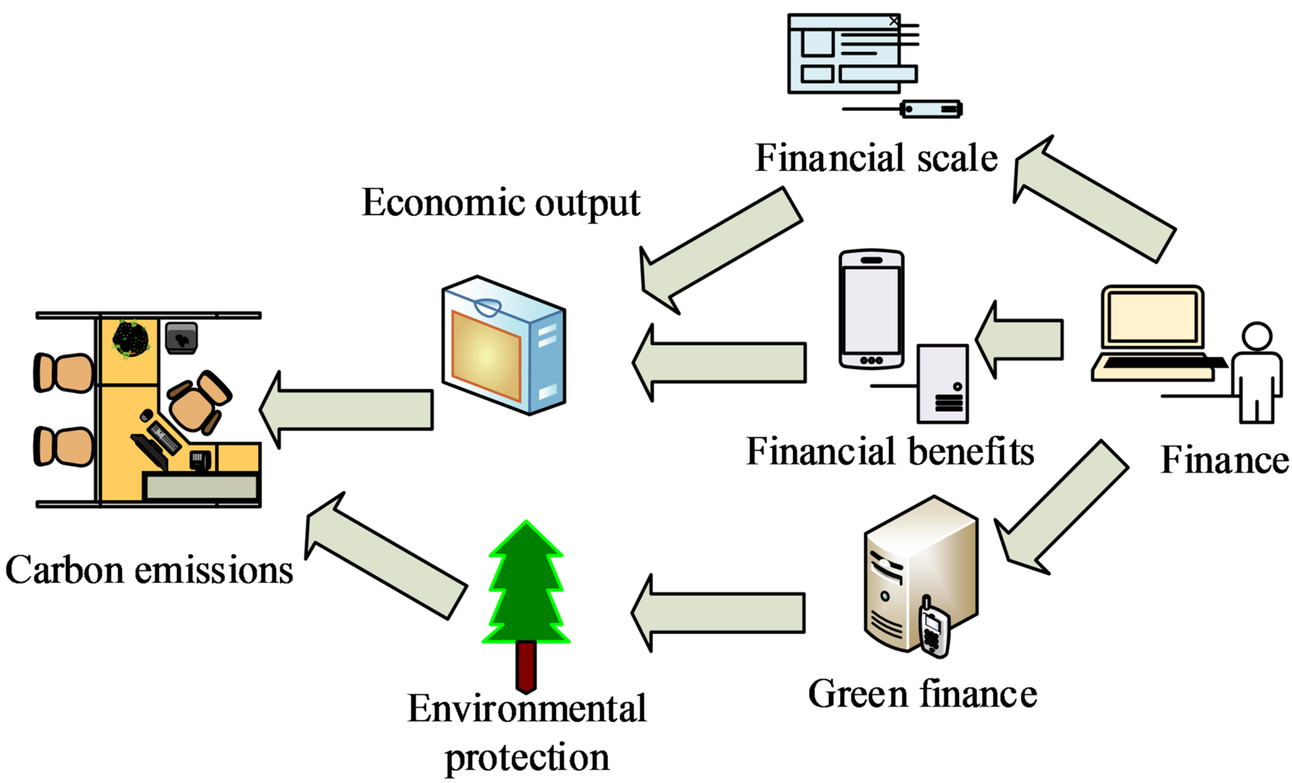

Fig. 3. The relationship between finance and CE.

In Fig. 3, the three financial indicators determine the changes in financial products and time environment. The financial scale and financial efficiency determine the output of financial products. Financial benefits and GF determine the environmental protection situation. When the financial economy increases, the CE of the environment also increases, leading to a deterioration of the regional environment. The implementation of carbon standards and carbon neutrality simultaneously will promote the reduction of environmental CE in the local area. Therefore, to achieve a higher level of financial economy and CE standards, it is possible to guide the flow of financial benefits, improve the utilization of funds, and develop more innovative products. Under the condition of unchanged financial scale, the CE of the region can be reduced by guiding financial benefits towards environmental protection. In the process of financial development, financial support is indispensable, and both technological innovation and enterprise development require sufficient financial support[19]. The development of financial scale also requires sufficient financial support. Figure 4 shows the main influencing factors of financial scale development.

In Fig. 4, the expansion of financial scale may lead to changes in the current financial models of enterprises and regions, including more diversified financial channels and more diverse financing channels[20]. Financial services for enterprises or regions have become more convenient. Innovating financial technology can also effectively expand the scale of finance, but meanwhile, it can also lead to increased operating costs and decreased efficiency for enterprises or regions. Diversified financial channels, convenient financial services, and innovative financial technologies can effectively promote economic development, enhance economic productivity, and reduce CE. However, the disorderly expansion of financial scale can also lead to increased operating costs and reduced management effectiveness for enterprises, resulting in a decrease in production capacity, which further increases CE. GF supports various financial activities and services related to SD, climate change, and resource conservation. GF mainly guides funds to projects that contribute to green infrastructure construction through financial instruments and mechanisms, thereby promoting economic sustainability[21]. Figure 5 shows the main measures and impact changes of GF.

In Fig. 5, GF mainly improves the efficiency of economic resource utilization by innovating financial technology during the implementation process. Technological innovation can not only directly reduce energy consumption of enterprises, but also reduce the use of pollutants in technology[22]. Meanwhile, GF can also innovate financial supply to guide high polluting industries to develop towards LC industries, contributing financial support for LC industries to ensure the operation of LC enterprises and the market conversion efficiency. Secondly, GF guides the local public to invest in LC and environmentally friendly enterprises[23].

Model building

The random effects regression model and spatial panel data model were selected to analyze the impact of low-carbon policies on green finance, mainly because these models can more accurately handle individual heterogeneity and spatial correlation in panel data. The advantage of the random effects model lies in its ability to handle heterogeneity and estimation efficiency under certain assumptions, although it requires assumptions that individual effects are not correlated with explanatory variables, which may be limited in practical applications.

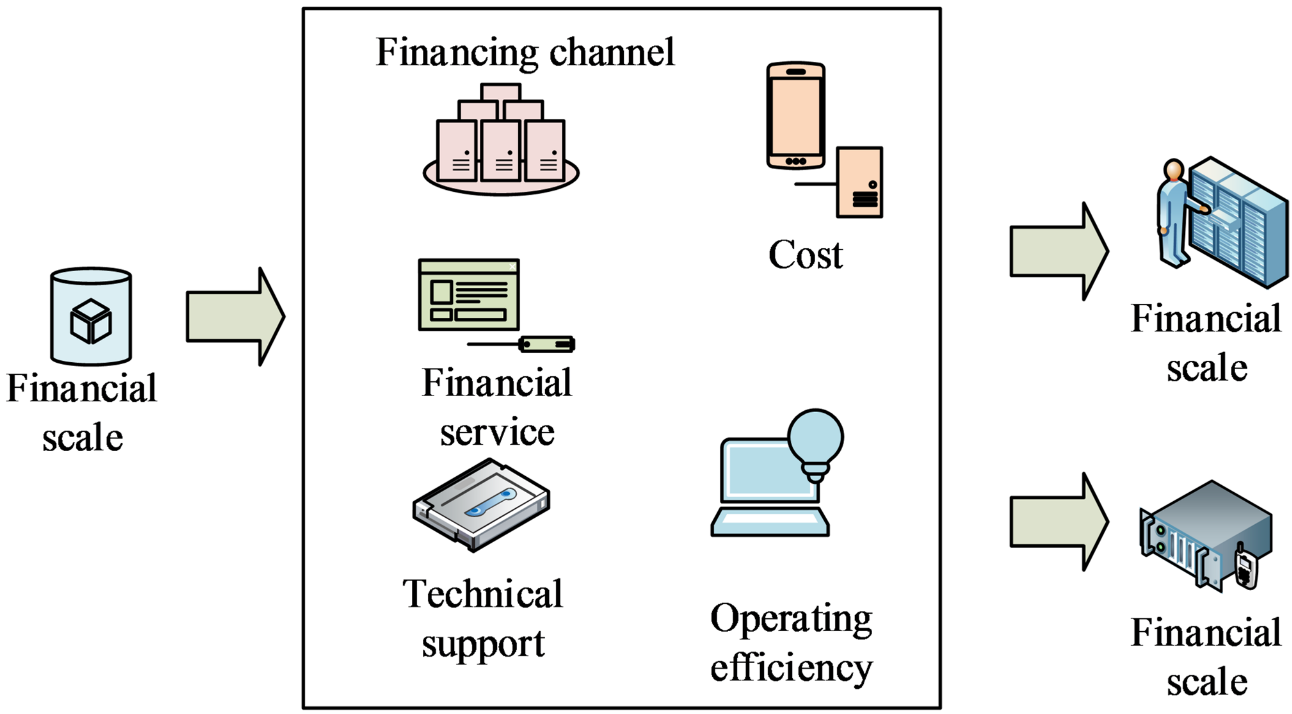

Fig. 4. Main influencing factors of financial scale development.

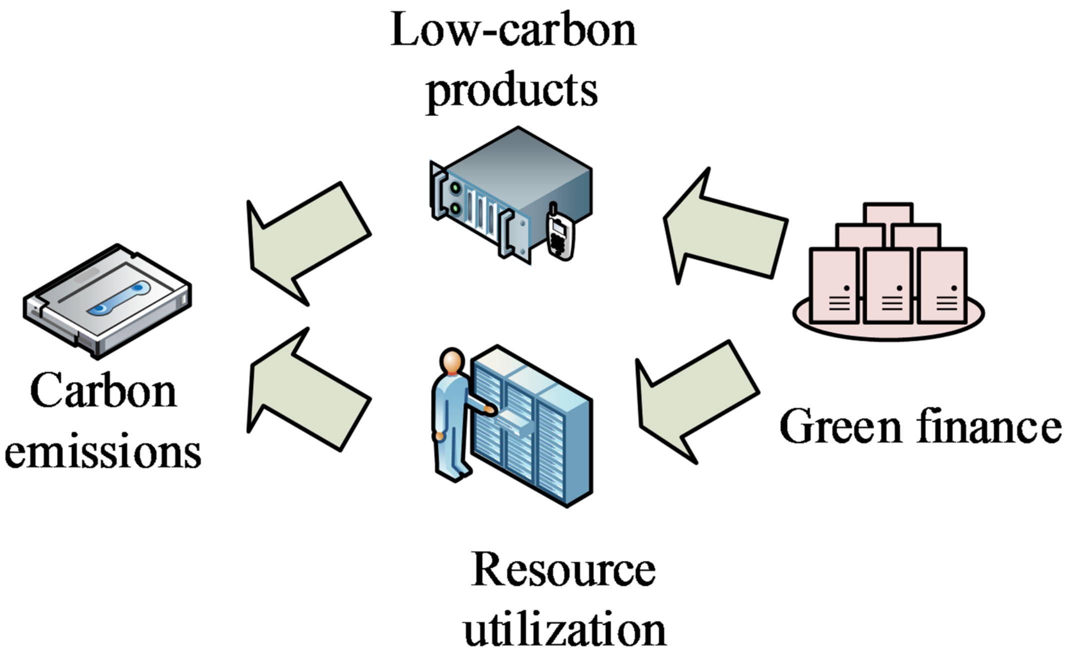

Fig. 5. Main measures and impact changes of green finance.

The spatial panel data model can capture the spatial dependencies of data and improve estimation accuracy, despite its high data requirements and complex model structure. Compared with fixed effects models, random effects models may have higher estimation efficiency in some cases, and compared with ordinary least squares regression models (OLS), these two models can more comprehensively handle the complexity of panel data, providing more accurate and reliable estimation results, especially when analyzing dynamic panel data with spatial dependence, showing significant advantages. This enables a deeper understanding of the impact of low-carbon policies on the development of green finance and their changes in different regions and times. The random effects model is based on the STIRPAT framework, introducing financial variables, assuming that individual effects are independent of explanatory variables, and ensuring data stationarity through LLC and IPS tests. The spatial panel model includes spatial autoregression (SAR) and spatial error model (SEM). The LM test is used to select the appropriate model, assuming a negative spatial correlation between carbon emissions and green finance. At the same time, there are limitations in the research, including limited data scope to the northwest region of China, incomplete resolution of endogeneity issues, possible neglect of geographical proximity effects in spatial weight matrices, insufficient capture of policy implementation differences, and limitations in the construction of green finance and carbon emission indicators. This study analyzes the impact of STIRPAT and SPD on green and LC orientation and GF development in high pollution areas. Equation (1) shows the influence of the basic coefficients of the model[24,25].

$$L_t = aP_t^b A_t^c T_t^d e_t. \tag{1}$$

In Eq. (1), L represents the concentration of pollutants; P, A and T represent the population size, economic and financial level, and technological level of the region. b, c and d all represent the elasticity coefficients of regional influencing factors; a represents the model coefficient; e_t represents the model bias value. The financial influencing factors are introduced into the model, resulting in Eq. (2).

$$LnY_{it} = Lna + b(LnP_{it}) + c(LnA_{it}) + d(LnA_{it})^2 + f(LnT_{it}) + g(LnS_{it}) + h(LnF_{it}) + e_{xt} \tag{2}$$

In Eq. (2), Lna is a constant, b, c, d, f, g, and h are all evaluation parameters for the influencing factors of regional CE; i represents cross-sectional units; Y represents CE; P represents population; A represents total production; S represents industrial structure; F represents regional financial support. Due to the influence of regional policies and ideologies on development concepts, the influence of regional policies is introduced into the model, resulting in Eq. (3)[26,27].

$$\begin{aligned} LnY_{it} = {} & Lna + b(LnP_{it}) + c(LnA_{it}) + d(LnA_{it})^2 + f(LnT_{it}) + g(LnS_{it}) + h(LnF_{it}) \\ & + j(LnF_{it} \times year) + e_{xt} \end{aligned}. \tag{3}$$

In Eq. (3), j represents the influencing factor parameter; F represents the policy variable; *year* represents the year; defined as 1 before 2012 and 1 after 2012. From this, three models were obtained for different regions through model changes, with modifications made to the impact of policy changes. The size of the financial scale is F^1; the impact of the size of financial benefits is F^2; the impact of GF size is F^3. SPD includes spatial autoregression and error models. Spatial autoregression is shown in Eq. (4)[28].

$$U=\rho WU+V\beta+\varepsilon. \tag{4}$$

In Eq. (4), U represents the dependent variable; V represents the variable matrix with a matrix size of $m*k$; W represents the weight matrix with a matrix size of $m*m$; m represents the number of regions; k represents the number of influencing factors; ρ represents the autoregressive coefficient of the model; WU represents the dependent variable of the model's retention space; ε represents the random error value; β represents the influence between variables. The spatial error of the model needs to be obtained by comparing the variables in adjacent regions with the observed effects in the current region, as shown in Eq. (5)[29].

$$\varepsilon=\lambda W\varepsilon+\mu. \tag{5}$$

In Eq. (5), λ represents the spatial error coefficient. When the size of the normal distribution error vector is μ, the expected budget symbol of the error is 0; the size of the random variance matrix of the error is $\sigma^2 H$, where H represents the identity matrix and σ represents the variance coefficient of the random variable. The effect variation of the fixed model is shown in Eq. (6).

$$U=\rho(H_T\otimes W)U+V\beta+\eta+\xi+\varepsilon. \tag{6}$$

In Eq. (6), H_T represents the time-dependent matrix; $\otimes$ represents the tensor product; η and ξ both represent fixed effects. The variation of the fixed error value is shown in Eq. (7).

$$\varepsilon=\lambda(H_T\otimes W)\varepsilon+\mu. \tag{7}$$

According to the above formula, all formula parameters and regional influences are included in the spatial model to obtain a fixed effects model as shown in Eq. (8).

$$\begin{aligned}LnY_{it}&=\rho(H_T\otimes W)LnY_{it}+b(LnP_{it})+d(LnA_{it})^2\\&+f(LnT_{it})+g(LnS_{it})+h(LnF_{it})+j(LnF_{it}\times year)+\eta_{it}+\xi_{it}+e_{xt}\end{aligned}. \tag{8}$$

At this point, the error variation of the model is shown in Eq. (9).

$$\varepsilon_{it}=\lambda(H_T\otimes W)\varepsilon_{it}+\mu_{it}. \tag{9}$$

In Eq. (9), if ξ_{it} and η_{it} are omitted, the SPD with fixed regional and temporal effects is obtained. In the CE calculation, since the industrial energy resources in the northwest region are mainly coal and oil, the calculation method is shown in Eq. (10)[30,31].

$$I_{xt}=\sum\nolimits_{r=1}^{m}E_{xtr}\times\xi_r. \tag{10}$$

In Eq. (10), I_{xt} represents the CE of fossil fuels in region x in year t; E_{xtr} represents the total energy consumption of r fossil fuels in the t-th year of region x; ξ_r represents the CE coefficient of fossil fuels r. The calculation formula for regional time year CE is shown in Eq. (11)[32,33].

$$I_t=\sum\nolimits_{x=1}^{n}I_{xt}. \tag{11}$$

In Eq. (11), I_t represents the CE of fossil fuels in year t.

Results

Green oriented financial development and CE status in high pollution areas

Due to historical reasons, some highly polluted areas such as the northwest region of China have mainly relied on heavy industry for economic development[34,35]. Overreliance on high carbon industries has led to insufficient resource utilization and excessive CE in the current development process of the region, exacerbating pollution problems and limiting regional SD. The carbon emission indices and financial data for the study come from a number of authoritative sources, including the China Energy Statistical Yearbook, China Environmental Statistical Yearbook, and China Financial Statistical Yearbook of the National Bureau of Statistics, the annual reports of local statistical bureaus and branches of the People's Bank of China, as well as relevant reports of the International Energy Agency (IEA) and the United Nations Environment Programme (UNEP). Carbon emissions are calculated through energy consumption data and internationally recognised carbon emission factors, covering major fossil fuels such as coal, oil and natural gas. Financial data, on the other hand, include indicators such as total assets, total loans, net profit and return on investment of financial institutions, as well as the proportion and number of investments in green financial products. The sample was selected from highly polluted areas in northwestern China, such as Gansu, Shaanxi, and Ningxia. The data for the regions in the study cover the period from 2001 to 2023, including before and after the implementation of the 'dual-carbon' policy. The data show that there are significant regional differences in carbon emission intensity, financial scale, financial efficiency, and green finance development in these highly polluted regions, and the overall development level is still lower than the national average. Taking the GF change index in the northwest region from 2021 to 2023 as an example, this study investigates the current development status of GF in high pollution areas. Table 1 shows the changes in GF Development Index in Northwest China from 2021 to 2023.

In Table 1, the changes in green indicators in the three regions were not significantly different. The green development index values of the three regions varied between 0.230 and 0.410, far below the national average level. This was because in the development of the three regions, the main economic development relied on heavy industry, resulting in more severe pollution to the areas. From the perspective of changes in the Green Development Index, Gansu Province's Green Development Index mainly relied on government support. The maximum environmental carrying capacity in Ningxia Hui Autonomous Region could reach 0.168. From the comparison of different years in the three regions, the green development index had significantly improved since 2021. This indicated that since the implementation of carbon neutrality in 2020, different regions had actively responded to the measures, with the financial core developing towards high-tech and new energy, reducing industrial pollution, and enhancing the environmental carrying capacity of the region. New environmental governance policies should be implemented in high pollution areas, with a focus on enhancing the industrial structure of enterprises, and efforts should be made to strengthen the research and growing of LC technologies in the region and improve resource utilization efficiency[36]. Figure 6 shows the changes in industrial pollution control in the northwest region from 2015 to 2023.

In Fig. 6 (a), the total investment in pollution control in the three regions was relatively low before 2015, with a total investment of only about 2.8 billion yuan in 2015. After 2015, the total investment increased from 2.8 billion yuan to 6.7 billion yuan in 2018. But after 2019, the investment amount began to decline and dropped to 3.8 billion yuan. After implementing carbon neutrality, the total investment increased to 10.8 billion yuan in 2023. In Fig. 6 (b), the growth rate of total pollution control investment decreased after reaching a small peak in 2018, and then showed a significant increase from 2020 onwards. With the expansion of investment in industrial pollution control in the northwest region, it promoted pollution control in the area and improved the green development indicators of the region[37,38]. According to the calculation formula for fossil fuels, the CE of high pollution areas is calculated and shown in Table 2.

In Table 2, the CE coefficient for all fossil fuels, except for natural gas, was kgc/kg. The conversion coefficient of standard coal varied with different fossil fuels, and the conversion coefficient of kerosene can reached 1.5126 at most. The CE coefficient of raw coal was the smallest, only 0.52485kgc/kg. From the perspective of fossil fuel structure, the emission of raw coal accounted for a relatively large proportion in the CE of the northwest region, indicating that the region mainly relied on the combustion of raw coal as its main resource for energy supply.

Analysis of financial status in highly polluted areas

With the implementation of the current "dual carbon" policy, governments in high pollution areas actively implemented various policies and guidelines issued. In recent years, the increase in residents' deposits in these areas led to stable financial and economic operations in the region. Figure 7 shows the trend of financial scale and deposit changes in the northwest region.

In Fig. 7, from 2001 to 2018, the deposit and loan changes in the highly polluted northwest region showed a stable growth trend. But during the period of 2019–2021, the deposit amount remained the same as the previous

	2021	2022	2023
Gansu Province			
Green development index	0.255	0.343	0.394
Economic growth greening degree	0.064	0.078	0.103
Resource and environment carrying capacity	0.068	0.089	0.092
Government policy support	0.123	0.176	0.199
Shaanxi Province			
Green development index	0.278	0.315	0.367
Economic growth greening degree	0.067	0.086	0.096
Resource and environment carrying capacity	0.086	0.094	0.104
Government policy support	0.125	0.135	0.167
The Ningxia hui autonomous region			
Green development index	0.235	0.337	0.408
Economic growth greening degree	0.054	0.064	0.071
Resource and environment carrying capacity	0.114	0.138	0.168
Government policy support	0.067	0.135	0.169
National average			
Green development index	0.348	0.425	0.535
Economic growth greening degree	0.146	0.168	0.216
Resource and environment carrying capacity	0.068	0.084	0.108
Government policy support	0.134	0.173	0.211

Table 1. Comparison of green indicator changes in high pollution areas from 2021 to 2023.

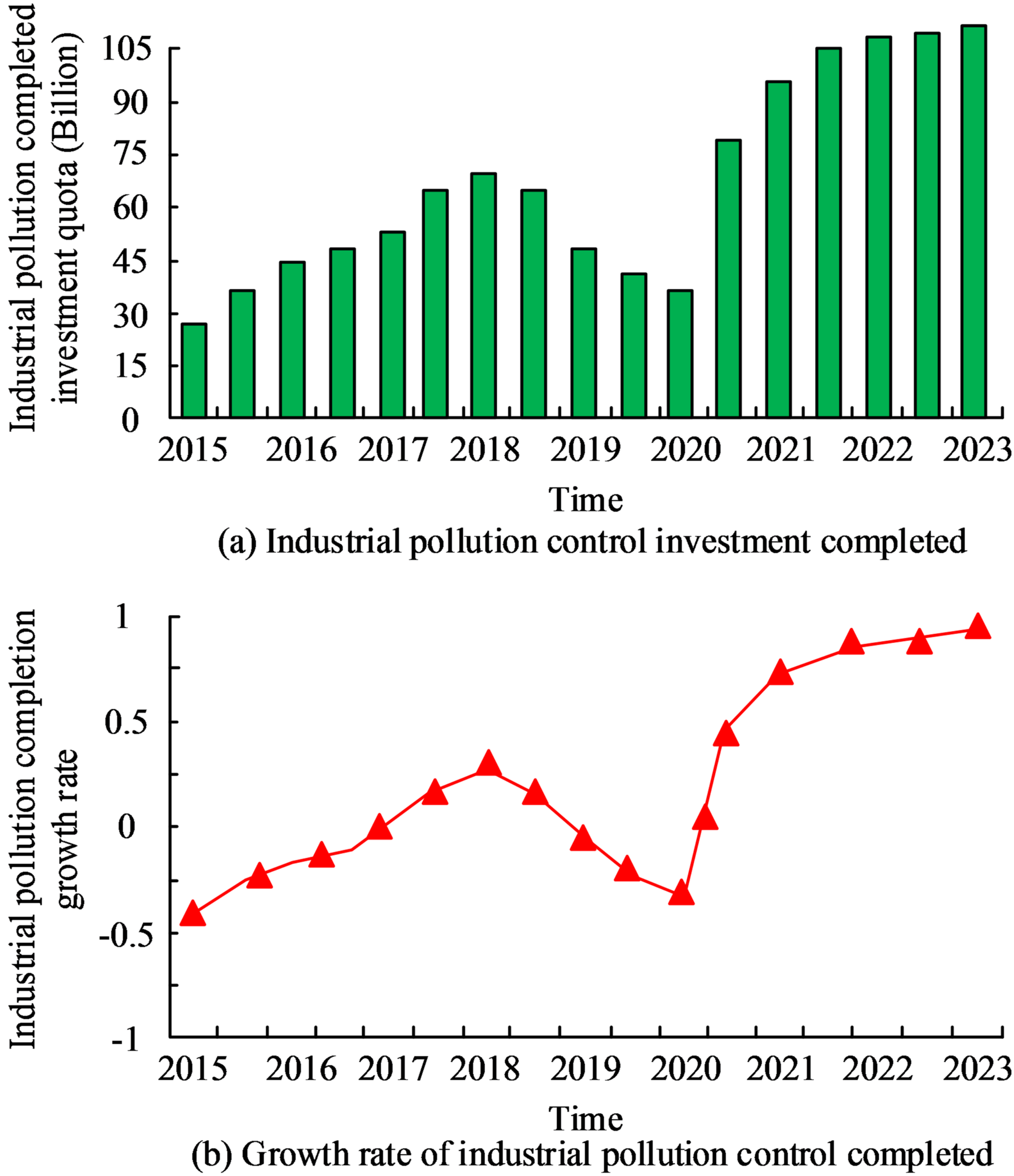

Fig. 6. Changes in total industrial pollution control in three regions.

period, while the loan amount increased. From 2001 to 2023, the deposit amount in the region increased from 0.78 trillion yuan to 382 million yuan, with a deposit amount growth of 3.04 trillion yuan. The loan amount increased from 0.69 trillion yuan in 2001 to 3.28 trillion yuan in 2023, a year-on-year increase of 2.59 trillion yuan. The overall financial scale of the region was expanding, and the rate of financial growth was steadily increasing. The current status of financial efficiency changes in highly polluted areas in recent years is shown in Table 3.

In Table 3, the changes in financial development efficiency in high pollution areas had been basically the same since 2001. The number of loans and deposits increased year by year with the increase of years. The growth rate

Fossil fuel	Conversion coefficient of standard coal	CE coefficient (kgc/kg, km^3)
Raw coal	0.6485	0.52485
Coke	1.0214	0.84856
Crude oil	1.3584	0.82548
Gasoline	1.4879	0.80158
Kerosene	1.5126	0.84862
Diesel oil	1.4451	0.85948
Fuel oil	1.4015	0.89152
Natural gas	1.1578	0.61581

Table 2. CE from high pollution areas in Northwest china.

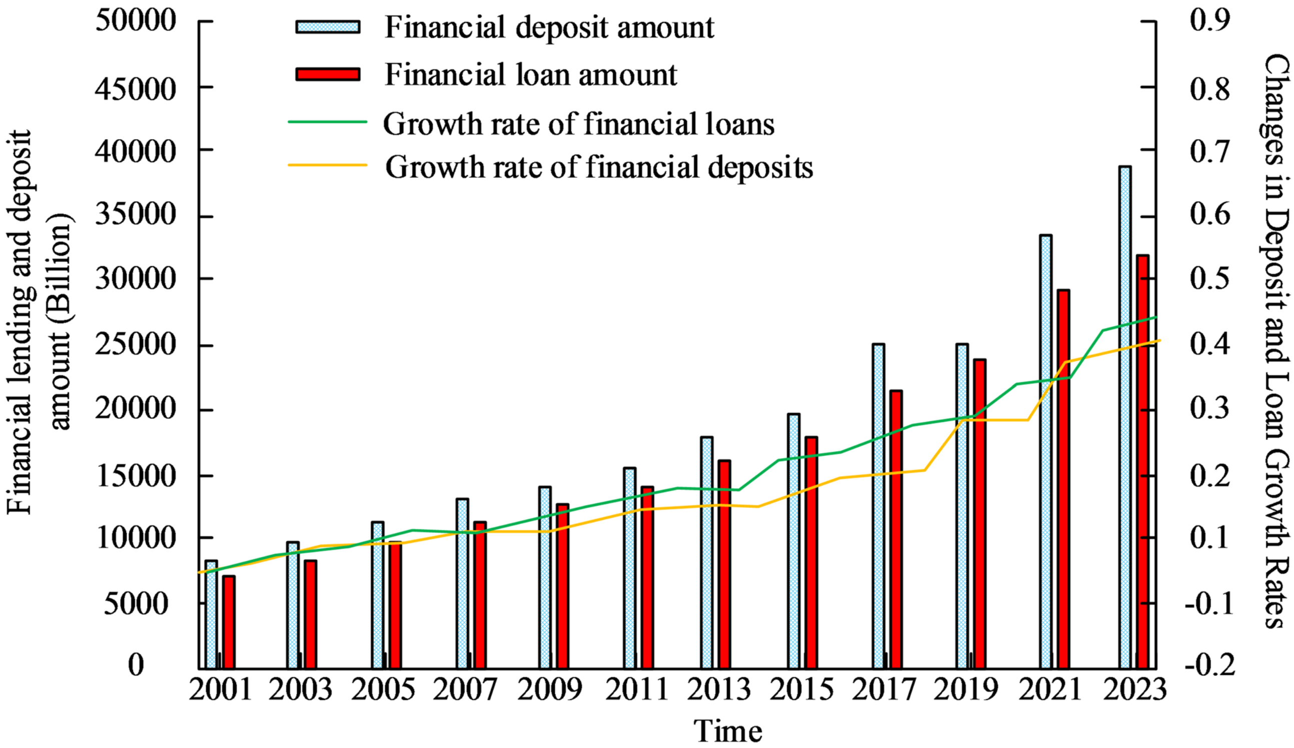

Fig. 7. Analysis of current status of financial deposits and loans.

Area		2001	2003	2008	2013	2018	2023	Average growth rate of deposits	Average loan growth rate
Gansu province	Deposit balance (billion)	1324.04	1816.02	3648.32	4658.32	5683.35	26485.36	16.84%	14.68%
	Loan balance (billion)	1241.12	1768.62	3235.64	4236.62	5426.84	24987.36		
	Deposit loan ratio	0.94	0.97	0.89	0.91	0.95	0.94		
Shaanxi province	Deposit balance (billion)	1425.62	1968.26	2486.28	11254.62	19683.25	24856.35	16.79%	15.18%
	Loan balance (billion)	1354.68	2015.36	2126.35	8765.25	16424.36	21586.59		
	Deposit loan ratio	0.95	1.02	0.86	0.78	0.83	0.87		
The ningxia hui autonomous region	Deposit balance (billion)	1254.36	1876.45	2015.36	4856.15	9658.21	11254.38	17.77%	17.03%
	Loan balance (billion)	1435.94	1758.62	1768.62	4536.84	9031.35	9486.34		
	Deposit loan ratio	1.14	0.94	0.88	0.93	0.94	0.84		

Table 3. Current situation of changes in financial efficiency in different high pollution areas.

	2009	2011	2013	2015	2017	2019	2021	2023
Gansu Province	386.24	204.36	248.31	254.74	546.32	1087.35	1354.25	4823.61
Shaanxi Province	148.62	223.84	284.24	268.35	1689.35	1542.36	1548.62	5236.35
The Ningxia hui autonomous region	675.32	254.38	345.24	635.25	642.54	2729.30	603.54	8654.31

Table 4. Proportion of total financial investment and industrial governance in highly polluted areas.

Variable	Sample size	Mean	Standard deviation	Minimum value	Maximum value
C	70	1780	1142	235.5	4622
Y	70	2015	1184	576	3978
GDP	70	19,035	8421	6035	34,463
O	70	987	2034	24	8902
V	70	0.465	0.0605	0.152	0.642
F^1	70	1.264	0.513	0.598	2.47
F^2	70	0.803	0.187	0.486	1.236
F^3	70	912.5	1403	91.35	9015

Table 5. General variable description.

of deposits in the three regions varied between 16.00% and 18.00%. The growth rate of loans varied between 14.00% and 18.00%. The loan to deposit ratios of the three regions fluctuated to varying degrees in different years. Overall, the loan to deposit ratio in the three regions was relatively small, which could not achieve a perfect financial investment situation. Personal income increased with the increase of years, but the development of financial investment concepts in the region was relatively poor. The financial development in this region was mainly based on deposit investment, and the level of financial development in the region was relatively backward. Meanwhile, small businesses found it difficult to obtain financial assistance through loans due to high local loan restrictions, which reduced the efficiency of financial capital utilization. In recent years, with the increasing implementation of government policies and more convenient transportation, the scale of financial markets in high pollution areas was gradually expanding, and the emerging regional development strategies had also provided convenience for regional development. Table 4 shows the proportion of total financial investment and industrial governance in high pollution areas.

By 2023, the proportion of total financial investment and industrial pollution control in the three regions could reach a maximum of 8654.31 times, which was a significant increase compared to 2009. Since 2019, the region had increasingly attached importance to economic and industrial pollution control, and the overall proportion analysis had been increasing year by year, which had promoted the growth of GF in the region and created better conditions for its development.

Empirical analysis of the impact of LC orientation on GF

Variable description

Due to differences in emission requirements among different policies in the model, the CE coefficient achieved in the model varied. Therefore, in this study, the average value was taken for judgment. The current CE coefficient was set at 3.20 tons, and the CE situation of different fossil fuels was calculated according to the CE coefficient standard in Table 2. Obtain variable descriptions as shown in Table 5.

In Table 5, the total CE was C, the total population of the region was Y, and the total economic growth index was GDP. The economic and financial industry structure of the region was V, and the level of economic and financial technology in the region was O. The financial support for the region included financial scale (F1), financial efficiency (F2), and GF (F3). This study explored the changes in financial scale based on the ratio of financial loans to per capita economic benefits, and defined financial benefits based on the ratio of financial loans to financial deposits. Finally, GF was defined based on the ratio of total financial loans to total pollution control.

CE stability test

To verify the current financial development situation in high pollution areas and the impact of CE, the CE size was subjected to model validation. To reduce the impact of specificity on the data, all data parameters in the model are logarithmically represented. Meanwhile, to reduce the probability of “false regression” in the model, the LLC test and IPS test methods are applied to verify the stationarity of the data obtained, see Table 6.

In Table 6, at a significance level of 10%, the variables CE total, regional total population, regional technological progress, and GF could be validated by horizontal units. The current variables were in a zero order equilibrium stable sequence state in the horizontal direction, so only one stage of verification was needed for the four variables of per capita economic growth, industrial structure, financial scale, and financial efficiency, and it was concluded that all four variables were first-order integrated sequences. In the model validation, except for industrial structure, financial scale, and financial efficiency, there were significant statistical differences ($P<0.05$) in the LLC validation results of other variables. Except for the total per capita economic growth, industrial

Variable	Test statistic (LLC)	*P*-value (LLC)	Test statistic (IPS)	*P*-value (IPS)
LN(C)	− 1.6152	0.0498	− 3.1548	0.0018
LN(Y)	− 4.4032	0.0001	− 4.6984	0.0000
LN(GDP)	− 6.1752	0.0000	0.7953	0.7965
LN(O)	− 4.2435	0.0008	− 2.5354	0.0057
LN(V)	− 0.3984	0.3534	0.605	0.7125
LN(F1)	2.9012	1.0254	3.426	1.0025
LN(F2)	1.4987	0.8762	1.2254	0.9025
LN(F3)	− 3.8942	0.0003	− 2.896	0.0008

Table 6. Results of stationarity verification for different variables.

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023
Geary's C	− 0.684	− 0.498	− 0.578	− 0.512	− 0.510	− 0.498	− 0.558	− 0.612	− 0.485
Z-value	− 1.902	− 1.603	− 2.065	− 1.638	− 1.298	− 1.698	− 1.893	− 1.843	− 1.258
P-value	0.042	0.061	0.026	0.057	0.086	0.042	0.027	0.033	0.115

Table 7. Geary's C index of highly polluted areas from 2015 to 2023.

structure, financial scale, and financial efficiency, there were significant statistical differences ($P<0.05$) in the IPS test for other variables.

Model correlation test

This study used the Geary's C model for statistical testing of spatial correlation, which can be used to evaluate the similarity or difference between local regions in spatial data, helping to reveal spatial structures and patterns in the data. The financial weight matrix was constructed as the reciprocal of the difference between the per capita economic growth value and the absolute value of per capita economic growth in a region. Table 7 shows the Geary's C index for high pollution areas from 2015 to 2023. Geary's C-index less than 0 indicates a negative spatial correlation between carbon emissions, meaning that a region's high carbon emissions tend to be associated with neighboring regions' low carbon emissions. This reflects the differences in economic development level, industrial structure, energy efficiency, and environmental policy implementation among different regions. At the same time, it should be noted that the effectiveness of different policies may vary in different regions, and adjustments need to be made according to the specific situation in each region. And negative spatial autocorrelation implies that carbon emissions between regions are interdependent. When formulating emission reduction policies, negative correlation suggests the need to consider the mutual influence and spatial dependence between regions, pay more attention to regional coordination and cooperation, and adopt differentiated strategies based on the characteristics of different regions.

In Table 7, in the current year analysis, the CEGeary's C index in high pollution areas was all less than 0, and there was a significant statistical change at the significance level of 10%. This indicated that there was a negative correlation between CE and spatial distribution in high pollution areas, and the CE situation in high pollution areas showed discrete changes in spatial distribution. There was no significant difference in the spatial CE distribution of different regions in high pollution areas, indicating that the CE of adjacent regions in high CE areas was lower, while the CE of adjacent regions in low CE areas was higher. This may be due to regional policy differences.

Spatial robustness analysis

The fixed benefit, time fixed, and time and benefit double fixed models in SPD were analyzed to verify the robustness of the model. The spatial error autocorrelation (LMerr) of the model was determined by the SEM model. The autocorrelation of the spatial lag model (LMsar) was analyzed for robustness using the SAR model. Table 8 shows the results of the model robustness analysis.

In Table 8, in Model (2), the statistical results of LMerr and R-LMerr were both greater than 0, but their statistical results were smaller than LMsar and R-LMsar. In the fixed time model, the statistical results of LMerr and R-LMerr − 5.4985 and − 0.1574 were both less than 0, which were less than the 16.5036 and 22.2584 of LMsar and R-LMsar. The LMerr and R-LMerr statistical results of the double fixed model were both greater than 0, 10.2485 and 2.1874, which were greater than the 8.2845 and 0.1542 of LMsar and R-LMsar. Therefore, based on the selection of the model, the current SEM model was better able to statistically analyze the true situation of the data.

Low carbon orientation and GF regression analysis in high pollution areas

In Table 8, model regression data analysis was conducted on CE in high pollution areas. According to the actual effect of the model, the LC orientation and financial regression situation in high pollution areas had been calculated, as shown in Table 9. In Table 9, the regression fitting degree of the current model was above 96%, indicating that the fitting degree of the model was more in line with the actual situation.

Model characteristics	LMsar	*R*-LMsar	LMerr	*R*-LMerr	Selected Model
Model (1) regional fixed effects	− 0.0008	− 0.0013	0.0256	0.0125	SEM
Model (1) time fixed effect	9.5984***	0.8963	12.2014***	3.5035*	SEM
Model (1) double fixed effect	8.7845***	2.0542	8.9485***	0.0548	SAR
Model (2) regional fixed effects	0.3752	0.1563	0.7120	0.512	SEM
Model (2) time fixed effect	− 5.4985	− 0.1574	16.5036***	22.2584***	SEM
Model (2) double fixed effect	10.2485***	2.1874	8.2845***	0.1542	SAR
Model (3) regional fixed effects	− 0.0028	− 0.0011	1.0264	1.0256	SEM
Model (3) time fixed effect	0.0001	0.0000	16.5485***	16.5254***	SEM
Model (3) double fixed effect	11.245***	2.0125	9.4856***	0.1051	SAR

Table 8. Results of model robustness analysis. *Significance level of 1%. **Significance level of 5%. ***Significance level of 10%.

	Spatial error model		Temporal fixed effects		Double fixed effect	
Independent variable	Coefficient	*P*-value	Coefficient	*P*-value	Coefficient	*P*-value
LN(Y)	2.1025	0.0001***	0.5012	0.0000***	6.1254	0.0000***
LN(GDP)	3.4395	0.0159**	− 5.2958	0.0021***	9.152	0.0000***
LN(GDP)$^{\wedge 2}$	− 0.1684	0.1578**	0.3241	0.0002***	− 0.268	0.0001***
LN(O)	0.1485	0.0002***	0.1365	0.0651*	0.1762	0.0000***
LN(V)	1.2543	0.0001***	− 1.0526	0.0005***	0.8684	0.0000***
LN(F1)	− 0.2548	0.0698*	− 0.5123	0.0186**	0.2031	0.1125
LN(F1* Year)	0.3487	0.0008***	0.4986	0.0203**	0.0675	0.3748
Spatial automatic regression coefficient	0.1245	1.0264	− 0.8452	0.0000***	–	–
Spatial lag dependent variable	–	–	–	–	− 1.032	0.0000***
coefficient of determination	1.0351	–	0.9695	–	1.0264	–
Error Variance	0.0078	–	0.0081	–	0.0018	–
log-likelihood	71.5342	–	66.9848	–	94.7695	–

Table 9. Changes in financial scale regression situation.

	Spatial error model		Temporal fixed effects		Double fixed effect	
Independent variable	Coefficient	*P*-value	Coefficient	*P*-value	Coefficient	*P*-value
LN(P)	1.7581	0.0006***	0.4152	0.0021***	6.4285	0.0000***
LN(GDP)	2.6875	0.0586*	− 6.0485	0.0002***	11.5035	0.0000***
LN(GDP)^2	− 0.1251	0.0768*	0.3862	0.0000***	− 0.4903	0.0000***
LN(T)	0.1958	0.0000***	0.1532	0.0033***	0.1245	0.0002***
LN(S)	0.5058	0.0268**	− 1.1482	0.0014***	0.4684	0.0148**
LN(F2)	− 0.4684	0.0197**	− 0.4536	0.1769	− 0.4154	0.0176**
LN(F2 * Year)	0.2425	0.4362	− 0.1598	0.7128	0.2015	0.2984
Spatial automatic regression coefficient	0.1115	0.4125	− 1.0356	0.0000***	–	–
Spatial lag dependent variable	–	–	–	–	–	–
coefficient of determination	1.0256	–	0.9768	–	1.0356	–
Error Variance	0.0084	–	0.0015	–	0.0015	–
log-likelihood	67.6845	–	65.4853	–	94.3554	–

Table 10. Changes in financial benefit regression situation.

In Table 9, the estimated parameter values for the variation of financial scale parameters in the fixed financial time model were 0.2031 and 0.1125. The data parameter size was 0.0675, and the P-value size was 0.3748. The regression of financial benefits was compared and analyzed, as shown in Table 10.

In Table 10, the estimated parameter values for the parameter changes of financial benefits in the fixed financial time model were − 0.4154 and 0.0176. The data parameter size was 0.2015, and the *P*-value size was 0.2984. The green regression situation was compared and analyzed as shown in Table 11.

In Table 11, the estimated parameter values for the parameter change of GF in the fixed financial time model were − 0.0089 and 0.5365. The GF data parameter size was 0.0035, and the *P*-value size was 0.8125. Comparing

Independent variable	Spatial error model		Temporal fixed effects		Double fixed effect	
	Coefficient	*P*-value	Coefficient	*P*-value	Coefficient	*P*-value
LN(P)	1.8459	0.0008***	0.7025	0.0000***	6.1485	0.0000***
LN(GDP)	3.4251	0.0215**	− 1.8976	0.2985	10.3596	0.0000***
LN(GDP)^2	− 0.1628	0.0348**	0.1468	0.1035	− 0.0459	0.0000***
LN(T)	0.1684	0.0002***	0.0268	0.4036	0.1503	0.0000***
LN(S)	0.7024	0.0004***	− 0.3985	0.1245	0.6751	0.0000***
LN(F3)	− 0.0514	0.0385**	− 0.1025	0.0001***	− 0.0089	0.5365
LN(F3 * Year)	0.0025	0.5158	− 0.0502	0.3658	0.0035	0.8125
Spatial automatic regression coefficient	0.1985	0.1168	− 0.8976	0.0000***	–	–
Spatial lag dependent variable	–	–	–	–	− 1.0152	0.0000***
coefficient of determination	1.4286	–	1.0256	–	1.0184	–
Error Variance	0.0089	–	0.0024	–	0.0024	–
log-likelihood	68.5248	–	71.4849	–	92.2368	–

Table 11. Changes in the return of green finance.

Variable category	Parameter name	Initial parameter value	Change in value	Impact explanation
Financial scale	F1	0.2031	0.1125	Indicates an increase in the size of financial institutions' assets, potentially enhancing their investment capacity in green projects.
Financial returns	F2	− 0.0089	0.5365	Represents an improvement in the rate of return on green investments, possibly due to policy incentives or improved market conditions.
Green finance	F3	− 0.4154	0.0176	Shows a decrease in the supply of green financial products, but an increase in environmental benefits, likely due to increased product efficiency.

Table 12. Comparison of changes in green finance parameters.

Year	Green development index	Degree of economic growth greening	Resource and environmental carrying capacity	Government policy support
2021	0.30	0.05	0.07	0.10
2022	0.35	0.07	0.09	0.15
2023	0.40	0.10	0.12	0.20

Table 13. Changes in the development index of green finance in Hebei Province from 2021 to 2023.

the financial relationship analysis in the three tables, the interaction term between the financial industry structure and the policy variables in 2018 was positive, but the overall performance was not significant. This indicated that the current policies in high pollution areas had not effectively supported the CE of financial regions. Meanwhile, the development of GF in high pollution areas was still in its initial stage. Meanwhile, the GF changes in highly polluted areas were also limited by regional factors, resulting in a low overall development level and restricted industrial structure. To analyze the parameter changes of different green finance variables, a comparative analysis was conducted on the changes of different financial parameters, as shown in Table 12.

From Table 12, it can be seen that the maximum change in Financial Returns can reach 0.5365 among different changes in financial parameters. This indicates that low-carbon orientation in high pollution areas is more likely to affect the financial returns of the region. At the same time, in different changes in green finance parameters, both green finance and financial scale have significantly improved, with green finance increasing by 0.0176 and financial scale increasing by 0.1125. It can be seen that low-carbon orientation in high pollution areas can significantly enhance the development of green finance in the region. Table 13 shows the impact of low-carbon policies on green finance in Hebei Province from 2021 to 2023. The data are from China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Financial Statistical Yearbook, and the annual reports of Hebei Provincial Bureau of Statistics and Hebei Branch of the People's Bank of China.

As can be seen from Table 13, Low carbon policies have a significant promoting effect on the development of green finance. By implementing low-carbon policies, Hebei Province has not only reduced carbon emissions, but also promoted the development of green finance, providing valuable experience for other high pollution areas to learn from. The changes in green finance through policy analysis are shown in Table 14.

From Table 14, it can be seen that after implementing government policy measures, the green finance index in high pollution areas has significantly increased since 2020, with the most significant increase in 2023, with an overall growth of 0.12. It can be seen that implementing corresponding low-carbon policies and measures can effectively enhance the green finance index of the region.

Year	Green finance development index without policy impact	Green finance development index with low-carbon policy implementation
2019	0.3	0.3
2020	0.32	0.35
2021	0.34	0.40
2022	0.36	0.45
2023	0.38	0.50

Table 14. Changes in green finance in highly polluted areas.

Sensitivity of model settings: Comparison of fixed effects and random effects: By replacing the original random effects model with a fixed effects model, it was found that the regression coefficient of low-carbon policies on green finance decreased from 0.5365 to 0.4982 ($p < 0.05$), but still maintained a significant positive effect, indicating that model selection has limited impact on the core conclusion.

Adjustment of spatial weight matrix: The original weight matrix based on economic differences was replaced with a geographic distance matrix (such as the weight of adjacent provinces), and the Geary's C index remained significantly negative (-0.4021, $p = 0.032$), indicating a robust conclusion of spatial negative correlation.

Dynamic panel model supplement: Introducing the system GMM model to control endogeneity, the low-carbon policy coefficient is 0.5128 ($p < 0.01$), which is consistent with the results of the static model.

Sensitivity of variable selection: Removing the industrial structure variable (V): The low-carbon policy coefficient of the core variable slightly increased from 0.5365 to 0.5487 ($p < 0.001$), indicating that industrial structure has a relatively small impact on the results.

Introducing government environmental protection expenditure: After adding the variable "proportion of government environmental protection expenditure", the low-carbon policy coefficient remains significant (0.5214, $p = 0.004$), and environmental protection expenditure has a positive effect on green finance (0.2036, $p = 0.012$).

Replace green finance indicators: Use green bond issuance scale instead of the original index, with a low-carbon policy coefficient of 0.4872 ($P = 0.008$), consistent in direction but slightly lower in significance, possibly due to significant regional differences in the bond market.

Time period analysis (2001–2020 vs. 2021–2023): Before the "dual carbon" policy (2001–2020), the low-carbon policy coefficient was 0.2145 ($p = 0.052$), approaching the significance threshold. After the implementation of the "dual carbon" policy (2021–2023), the coefficient jumped to 0.6823 ($P = 0.001$), indicating an enhanced effect of the policy. Excluding abnormal years (such as the 2020 pandemic): The low-carbon policy coefficient remained stable at 0.5289 ($p = 0.003$), and the results were not significantly disturbed.

In the analysis of changes in financial scale, the positive coefficient of financial scale indicated that the current regional financial support had played a certain promoting role in the changes in financial scale. This may be due to the insufficient development of the local financial system and the imperfect financial mechanism. With the increase of financial scale, industrial development in high pollution areas had accelerated, and the use of fossil fuels has become more frequent, resulting in the current increase in CE. The coefficient change of financial benefits was negative, indicating that the current LC benefit support had a restraining effect on the impact of financial benefits. The improvement in efficiency represented a faster rate of financial conversion, indicating that the financial system in high pollution areas was gradually improving, and the market was more conducive to the development of LC, green and environmentally friendly industries. There was a negative correlation between GF and CE, with a low level of significance. This indicated that the current LC policies in the region had a certain promoting effect on the growth of GF, but the promoting effect was relatively small. This may be due to incomplete implementation of regional policies or a lack of incentive policies in the region.

Policy analysis

To further promote the development of green finance in high pollution areas, the current region should implement some emission reduction policies, such as formulating and updating low-carbon emission laws and standards. At the same time, provide tax exemptions, subsidies, and financial incentives for enterprises that adopt low-carbon technologies to reduce their operating costs and enhance their competitiveness. And invest in the research and development of low-carbon technologies, encourage cooperation between enterprises and research institutions, and accelerate the commercialization of innovative technologies. Finally, it is necessary to raise public awareness of low-carbon lifestyles and promote green consumption and low-carbon behavior through education and media promotion. And the government also needs to encourage banks and financial institutions to provide green credit and offer low interest loans for green projects. Attract venture capital and private equity funds to invest in green industries. Developing a green bond market to provide long-term financing channels for low-carbon projects. Finally, provide insurance products and guarantee mechanisms to reduce investment risks in green projects.

For green finance cooperation in different regions, it is necessary to establish regional green finance cooperation platforms to promote information sharing and exchange of best practices. And coordinate policies at the regional level to ensure consistency and complementarity of low-carbon financial policies. Simultaneously establish cross regional green investment funds to jointly invest in low-carbon projects and green infrastructure. Developing cross-border carbon trading markets, allowing for the trading of carbon emission rights between different regions, and promoting regional cooperation in carbon reduction.

Low carbon policies guide financial institutions to invest funds in low-carbon projects by setting clear emission reduction targets and incentive measures. If the government adopts carbon pricing mechanisms (such as carbon taxes and carbon trading markets) and green finance subsidy policies to reduce the financing costs of low-carbon projects and enhance their market attractiveness. Secondly, low-carbon policies have promoted innovation in green technologies and low-carbon transformation of traditional industries. Financial institutions provide financial support for these technological innovation and industrial upgrading projects through green loans, green bonds, and other means. Hebei has significantly reduced the carbon emission intensity per unit of GDP by supporting the technological transformation of steel enterprises through green credit. At the same time, low-carbon policies reduce investment risks in green finance projects by regulating market behavior and providing policy transparency. By establishing strict environmental standards and carbon emission regulation policies, the government has reduced investment risks in high carbon projects and guided funds towards low-carbon projects. Finally, low-carbon policies have increased society's awareness and importance of low-carbon development through publicity and educational activities, and strengthened market confidence in green financial products. The interaction coefficient between low-carbon policies and financial scale is 0.0675, indicating that under the guidance of low-carbon policies, the expansion of financial scale has a more significant promoting effect on green finance. In summary, low-carbon policies have a significant promoting effect on green finance through various mechanisms, which are specifically reflected in the model parameters and provide scientific basis and practical guidance for policy makers and financial institutions. The increase in financial scale (value of 0.2031) implies that financial institutions have more funds to invest in green projects, thus promoting the development of green finance, and for every unit increase in financial scale, the green finance development index increases by 0.1125 units accordingly; the increase in financial efficiency (value of -0.0089) indicates that the use of funds is more efficient, which helps to optimise the allocation of resources, so that more funds flow towards green and low-carbon projects, and for every unit increase in financial efficiency, the green finance development index increases by 0.5365 units, showing its significant positive impact on the development of green finance; while the negative parameter value of green finance (-0.4154) may reflect a decrease in the supply of green financial products, but this decrease may be due to the increase in the efficiency of the products, i.e., an increase in the environmental benefits that each product can bring, and for every unit increase in green finance, the green finance development index increases by 0.0176 units, suggesting that its positive impact on green finance development is small but still significant.

To promote low-carbon transformation and green financial development in high-pollution areas, it is recommended that a green bond market be established at the policy level to reduce issuance costs through tax incentives and subsidies, and that regulation and information disclosure be strengthened to ensure that funds are used for low-carbon projects. Then implement a carbon tax and establish a carbon trading market to raise the cost of high-carbon products through carbon pricing tools to push enterprises to reduce emissions, and provide technical assistance and training to help them adapt to the policy. In industrial centres, industrial upgrading and technological innovation should be promoted, low-carbon industrial parks should be built, and regional cooperation should be strengthened for optimal allocation of resources. In other areas, emphasis should be placed on promoting green buildings, low-carbon transport and green agriculture, while public awareness of low-carbon living should be raised through education and publicity campaigns.

Conclusion

This study analyzes the impact of LC orientation in high pollution areas on GF. By using STIRPAT and SPD to analyze the financial scale, financial benefits, and three financial factors of GF, the study explores the influence of three variable factors on the development of GF in high pollution areas. This study establishes STIRPAT and SPD, and uses different data validation models to verify GF data in high pollution areas. At a significance level of 10%, the total CE, regional population, regional technological progress, and GF variables passed the unit root test in the horizontal direction. In the analysis of years, the Geary's C index of CE in high pollution areas was all less than 0, and there was a significant statistical change at the 10% significance level. In the fixed time model, the statistical results of LMerr and R-LMerr were −5.4985 and −0.1574, which were smaller than the 16.5036 and 22.2584 of LMsar and R-LMsar. In the fixed financial time model, the estimated parameters of financial scale were 0.2031 and 0.1125. The parameter values of financial benefits were −0.4154 and 0.0176, respectively. The product parameter of GF's benefit variable and policy variable was 0.0035, with a P-value of 0.8125. Therefore, the LC orientation in high pollution areas can significantly promote the development of GF in the region, reduce regional CE, and attract more funds to flow into the GF industry. Although some achievements have been made in the research, there are still some shortcomings. The study only analyzed data from recent years in the region, so it is necessary to broaden the analysis of data from more regions. Meanwhile, further research and use of more models are needed to explore the LC direction for the future.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Received: 28 October 2024; Accepted: 28 May 2025
Published online: 01 July 2025

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Author contributions
Yunyan Yang processed the numerical attribute linear programming of communication big data, and the mutual information feature quantity of communication big data numerical attribute was extracted by the cloud extended distributed feature fitting method. Yunyan Yang Combined with fuzzy C-means clustering and linear regression analysis, the statistical analysis of big data numerical attribute feature information was carried out, and the associated attribute sample set of communication big data numerical attribute cloud grid distribution was constructed. Yunyan Yang did the experiments, recorded data, and created manuscripts. All authors read and approved the final manuscript.

Funding
The research is supported by: Anhui Province University Research Program Project: Mechanism and Effects of Digital Finance in Promoting High Quality Economic Development in Anhui Province under the New Development Pattern (2022AH051730).

Declarations

Competing interests
The authors declare no competing interests.

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