Green financial development efficiency: a catalyst for driving China's green transformation agenda towards sustainable development

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RESEARCH ARTICLE

Green financial development efficiency: a catalyst for driving China's green transformation agenda towards sustainable development

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Abstract
The pursuit of a green transformation agenda in China is an important aspect of achieving sustainable development. The role played by green financial development efficiency (GFDE) in this pursuit cannot be overlooked. This paper explored the impact of GFDE on China's green transformation agenda and its contributions toward sustainable development. The study adopts a systematic approach to examine the relationship between GFDE and green transformation, utilizing relevant data and literature. The study aligns with previous research in the field that highlights the importance of green finance in reducing carbon emissions and promoting sustainable development in China. It also adds to the existing literature by specifically focusing on the role of green financial development efficiency in the pursuit of a green transformation agenda in China. The study found a significant improvement in GFDE over the period of 2010 to 2020 in promoting green transformation in China. Both systems generalized method of moments and fixed-effect models revealed that trade openness, foreign investments, technological innovation, and government budget positively influenced GFDE while energy consumption and economic policy uncertainty had a significant adverse effect on GFDE. The results of this study inform policymakers and stakeholders of the importance of green finance in promoting sustainable development. The study intimated that the financial sector should provide support for green technologies and businesses by offering range of green products such as green bonds, funds, and loans.

Keywords Green Finance · Green financial development efficiency · Green transformation · Sustainable development · sGMM

Introduction

Green transformation is a vital aspect of sustainable development, with China as a leading country pursuing this agenda (Cui et al. 2022). The country has been experiencing rapid economic growth in recent years, but this growth has been accompanied by environmental degradation, natural resource depletion, and other ecological challenges (Xu and Gao 2022). Green financial development plays a vital role in supporting this transition by providing the necessary financial resources and support to drive green investments and promote the adoption of sustainable practices (Li et al. 2022c).

The role of green finance in sustainable development has been well established, as it enables the mobilization of capital towards environmentally and socially responsible investments (Wu 2022). However, China's green finance development is still in its infancy compared to western developed countries, with a lack of infrastructure, lagging laws, and a need for increased understanding among financial

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institutions and enterprises (Li and Fan 2022). This paper proposes an index system and dynamic regression model to analyze the level of green finance development in China from 2010 to 2020 and identify factors influencing regional differences (Gu et al. 2021; Zheng and Dong 2021; Dong and Xu 2022; Zhou et al. 2022).

Financial and economic factors such as economic development, foreign investment, trade openness, education, and urbanization are factors that influence the level of green finance development in a region (Zhang et al. 2022a; Musah et al. 2021d; Li et al. 2021; Li et al. 2022a, b, c). This has helped to ensure that green finance is effectively integrated into the broader financial system, contributing to a more sustainable and eco-friendly growth path. The government has established institutions such as the Green Finance Committee to promote green finance and ensure its integration into the broader financial system (Li et al. 2022c). China's rapid economic growth has come at a cost to the environment, and the challenge is to balance economic development with environmental protection (Zhou and Xu 2022). The "14th Five-Year Plan" recognizes the negative impacts of previous economic growth on the environment and emphasizes the need for a development approach that prioritizes both economic growth and environmental protection (Gu et al. 2019; Gu et al. 2021; Guo et al. 2022).

Green transformation is crucial for sustainable development in China, and green finance plays a significant role in driving this transition by providing financial resources and support for sustainable investments (Xu et al. 2022a). The government is taking measures to promote green finance and balance economic development with environmental protection, but further work is needed to address the challenges facing China's green finance development. The plan calls for a development approach based on the principle of "green water and green hills are the silver mountain of gold," which prioritizes both economic growth and environmental protection. In conclusion, pursuing the green transformation agenda in China is crucial for achieving sustainable development, and green finance plays a significant role in driving this transition. By leveraging the power of financial markets, green finance provides the necessary financial resources and support to promote environmentally and socially responsible investments, helping to reduce the ecological footprint of economic activities and contribute to sustainable growth. Hence, the study sought to investigate the role of green financial development efficiency in the sustainable development of China.

The significance and innovation of this study can be further highlighted. This study advances our understanding of the impact of green financial development efficiency (GFDE) on China's green transformation agenda and its contribution to sustainable development. While previous study on green finance development efficiency focused on estimating GFDE, this study further investigated the influencing factors that affected GFDE improvement and growth in China. In order to ensure endogeneity of the results, control variables were inculcated in the regression analysis which was not considered in previous studies. Furthermore, in this study, a systematic evaluation methodology is employed, incorporating the generalized method of moments (GMM) system and a fixed-effect model. This approach allows for a robust examination of the relationship between Green Financial Development and the transformation towards a more sustainable economy in China, as reflected in financial and economic indicators. Not only above, but also the study adopted the fixed-effect model as robust check to determinant how the influencing factors influenced GFDE in China. Sub-group analysis was done for all the four main sectors in China to provide comprehensive understanding of the determinants of GFDE in China. The findings have important implications for policymakers and stakeholders in the field of green finance and sustainable development, as they highlight the significance of green finance in promoting sustainable development and the role of GFDE in achieving a green transformation agenda. Moreover, the study identifies barriers to green finance and underscores the need for further research to address these limitations and improve the efficiency of green financial development. This study represents a valuable contribution to the existing literature on green finance and sustainable development, providing novel insights into the specific role of GFDE in the pursuit of a green transformation agenda in China. The study was guided by research questions such as (1) *Is the regional GFDE in China is slowly improving*? (2) *Does trade openness, industry structure, FDI, innovation, human capital, government budget, and government effectiveness influence GFDE within the regions of China?* The paper comprises of five sections. "Literature review" section provides a literature review of prior studies. "Data envelopment analysis (DEA)" section outlines the methodology of the study. "Analysis of influencing factors of green financial development toward sustainable development" section presents and discusses the results. "Conclusions, recommendations, and limitations" section summarizes the study, offering conclusions based on the findings.

Literature review

Sustainable Development Theory

The evolution of the theory of Sustainable Development (SD) has been influenced by practical implementation and policy implementation (Steer and Wade-Gery 1993; Deng 2007). It has progressed from a simple idea to a global strategic issue (Olawumi and Chan 2018) and has been divided into three phases by scholars: embryonic (pre-1972), molding (1972–1987), and developing (since 1987) (Niu et al. 2015; Broman and Robèrt 2017). However, there is still a lack of understanding of SD in academia, government, and businesses (Niu et al. 2015; Broman and Robèrt 2017). The interpretations of SD are shaped by various organizations and do not fully reflect its holistic concept (Jingzhu et al. 1999; Robert et al. 2005). There is a need to revisit the definition of SD and establish a more comprehensive one (Hedenus et al. 2018).

The theory and practice of SD are interlinked and cyclical, influencing each other (Niu 2012; Steer and Wade-Gery 1993). The theory guides the practice and is refined through its implementation (Niu 2012). A literature survey and induction analysis are used in this paper to gather information on the theory and practice of SD, and a normative analysis is used to draw conclusions based on existing SD theories (Beggs 2019). This study builds on a comprehensive review of the theory and practice of Sustainable Development (SD), including its various types and objectives. Based on this review, several important topics in current SD research will be scrutinized and analyzed. The aim is to use scientific methodologies to establish clear objectives and draw testable conclusions (Beggs 2019; Musah et al. 2021b). It should be noted that SD theory differs from traditional development theories as it places a greater emphasis on meeting current needs while also considering future generations and ensuring that resources are not depleted. The three main characteristics of SD theory are equity, sustainability, and commonality.

The relationship between equity, sustainability, and commonality and the efficiency of green finance development can be described as follows: Equity and sustainability serve as guiding principles for green finance development and contribute to its efficiency by ensuring inclusiveness and accessibility (equity) and prioritizing environmental protection (sustainability) (Niu 2012; Musah 2022). The principle of commonality emphasizes the importance of international cooperation in addressing environmental challenges, enhancing the efficiency of green finance development by pooling resources, and achieving common environmental goals (Hedenus et al. 2018; Agyemang et al. 2021). The SD solidifies the need for green financial activities that are geared towards improving the environment through investment practice such as green financing, hence the need to investigate how the driving forces of GFDE in China as a catalyst for driving China's green transformation agenda towards sustainable development.

Green financial development

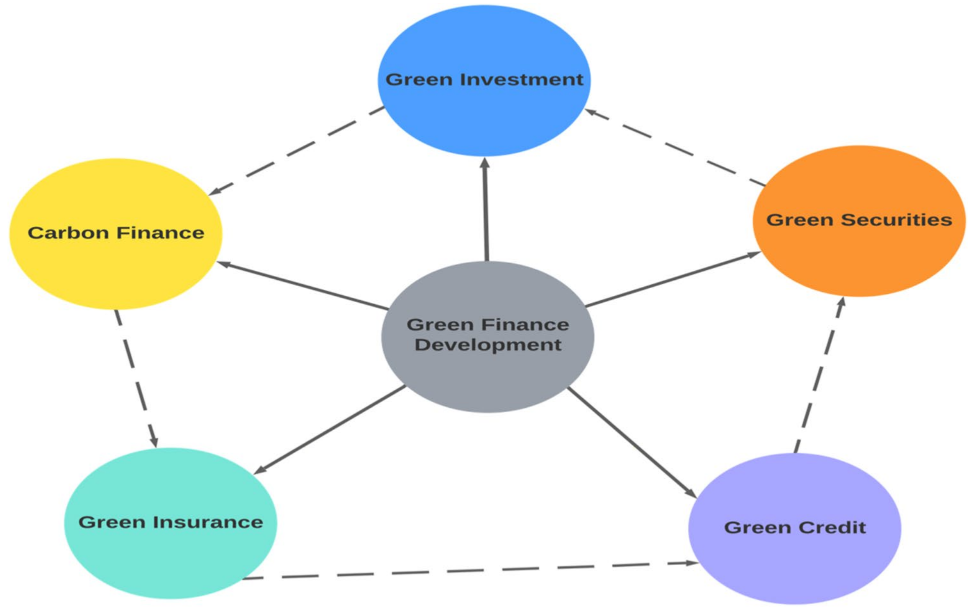
Green finance, which refers to the integration of sustainable development principles into financial decision-making and the use of financial means to shift towards sustainable production methods, was first introduced by Cowan (1999) as a link between the environment and finance and as a means of environmental protection through financial innovation. Labatt and White (2002) see green finance as a combination of environmental protection and financial innovation, while Zadek and Flynn (2014) considers it as a more extensive and difficult-to-measure concept than just investments in green projects. Researchers such as Yang and Ni (2022) and Berensmann and Lindenberg (2016) stressed the importance of government and private green investments, environmental policies, and green financial institutions in supporting green finance. Jianliang (1998) and Chen et al. (2022a, b) highlight the role of green finance in promoting the development of green enterprises and implementing economic and environmental policies.

Bohong (2009) argued that green finance can drive growth in environmentally responsible businesses and curb businesses that pollute, thus promoting sustainable economic growth. Zhou et al. (2022) see the development of green finance as a response to both external and internal demands for environmental protection and sustainable economic growth, respectively. For instance, Lv et al. (2021a, b) describe green finance as a combination of top-down and bottom-up approaches, with China's development of green finance primarily driven by government initiatives.

Assessing the progress of green finance remains a developing field (Jianliang 1998), with evaluations focused primarily on its growth and success. Studies have shown that the availability of green financial instruments significantly influences the level of green financial development in a region (Scholtens and Dam 2007; Musah et al 2022a). Areas with more comprehensive green finance systems tend to have higher levels of green financial development (Li and Pan 2012). Green finance, as a rapidly growing field, encompasses a range of products that prioritize environmental sustainability and social responsibility. The five main types of green finance-related products are green investment, green credit, green securities, green insurance, and carbon finance, (Wang and Wang 2022) as illustrated in Fig. 1.

(a) Green investment, also referred to as "socially responsible investment," prioritizes environmental, social, and financial returns. It is an investment strategy aimed at balancing the interests of people and the natural environment and focuses on environmental protection, resource conservation, and ecological construction (Li and Pan 2012). In contrast to traditional investment models, green investment incorporates environmental sustainability and social responsibility into the investment and reinvestment processes (Hu et al. 2020).
(b) Green credit involves the evaluation and financing of commercial and policy banks, as well as the relaxation

Fig. 1 Types of green finance



of financing restrictions for businesses in compliance with environmental protection policies and the tightening of restrictions for those that violate such policies, thereby guiding economic and social development (Wang and Wang 2022).

(c) Green securities, as a component of green finance, regulate the investment of funds raised by listed companies, establish environmental protection systems and performance evaluations, and promote investment in environmentally friendly industries (Xu and Gao 2022; Shao et al. 2021). This integration of environmental protection with the financing system helps to curb the inflow of funds into highly polluting and energy-intensive industries while promoting the transition to eco-friendly economic and social development (Zhang et al. 2022a).

(d) Green insurance compensates policyholders for damages caused by environmental accidents and reduces business risk, while also serving as a means for the insurance industry to fulfill its social management role and for victims to receive quick compensation (Labatt and White 2002).

(e) Carbon finance plays a critical role in transitioning China's economy from high carbon to low carbon and is essential to achieving the goals of a carbon peak by 2030 and carbon neutrality by 2060 (Li et al. 2022c). It encompasses investment and financing activities aimed at mitigating and adapting to climate change (Labatt and White 2002), and may refer either broadly to these activities, or narrowly to financial derivatives such as futures and options on carbon emission rights (Ba 2022; Yang 2021).

The theoretical mechanisms guiding the study of green finance development were further discussed in the next section.

Theoretical mechanism of green financial development

Finance can be defined as the provision of capital and serves several functions in economic growth, including the aggregation of production factors (Ba 2022) and the enhancement of capital productivity through improved investment and financing efficiency (CICC Research 2022). Green finance, a subsidiary of traditional finance, merges finance with environmental sustainability. It uses green financial instruments and derivatives, such as green bonds and green credit, to support environmentally friendly industries and foster economic growth (Shi et al. 2022).

The development of green finance has been seen as a crucial aspect of addressing the environmental issues while promoting sustainable economic growth (Hou et al. 2023; Xie et al. 2022). The Chinese government has recognized the importance of green finance and has taken several steps to support its development. In June 2017, five provinces were selected as pilot zones for green financial reform and innovation to explore replicable and extendable experiences (Lu et al. 2022). Policies such as tax breaks and credit subsidies are being put in place to make green financial reforms more affordable and targeted in these pilot zones (Zhang et al. 2022a).

However, the development of the green finance market in China faces some challenges. The rapid pursuit of economic development and ecological environmental protection leads to contradictions, and the government's capital is not enough to meet the rapid development of the green financial market. Financial institutions such as commercial banks, policy banks, and securities companies need to work together to provide a steady flow of funds to help the green financial market grow (Ba 2022). Moreover, the level of green finance development varies from place to place, depending on the level of investment in green financial development and the level of regional economic development (Xie et al. 2022).

The rapid growth of the domestic economy has led to changes in economic development factors, including environmental resources, natural resources, and human resources (Fu and Ng 2020; Wang and Wang 2022; Musah et al. 2021c). Establishing green finance can help bridge the gap between economic development and environmental resources and bring about the green transformation of the economic structure (Gu et al. 2019). On the one hand, it can help direct social capital investment towards green projects that maximize social welfare and create new economic growth points (Wang et al. 2021). On the other hand, it can help the green industries transition from traditional environmental consumption-based economic growth to green economic growth driven by technology (Li and Pan 2012; Peng and Zheng 2021).

The development of green finance is crucial for achieving sustainable economic development while addressing environmental issues. The Chinese government's support, financial institutions' collaboration, and policies aimed at promoting green finance can help overcome the challenges and bring about the green transformation of the economy. Further research into the influence of the level of regional economic development on the development of regional green finance can provide valuable insights into the process of reconciling economic development with the protection of the ecological environment (Xiao et al. 2022; Gu et al. 2019). The main research objective of this study is to analyze the influencing factors of the level of green financial development in China period of 2010–2020. Based upon the extensive review of literature, a theoretical framework was designed to guide the study forming the theoretical mechanism that governed the study (Fig. 2).

Indexing of green financial development efficiency

The present study aimed to investigate the green financial development efficiency in 30 provinces of China. The indexing of GFDE was guided by previous research on the subject, including studies conducted in China (Wang et al 2021;

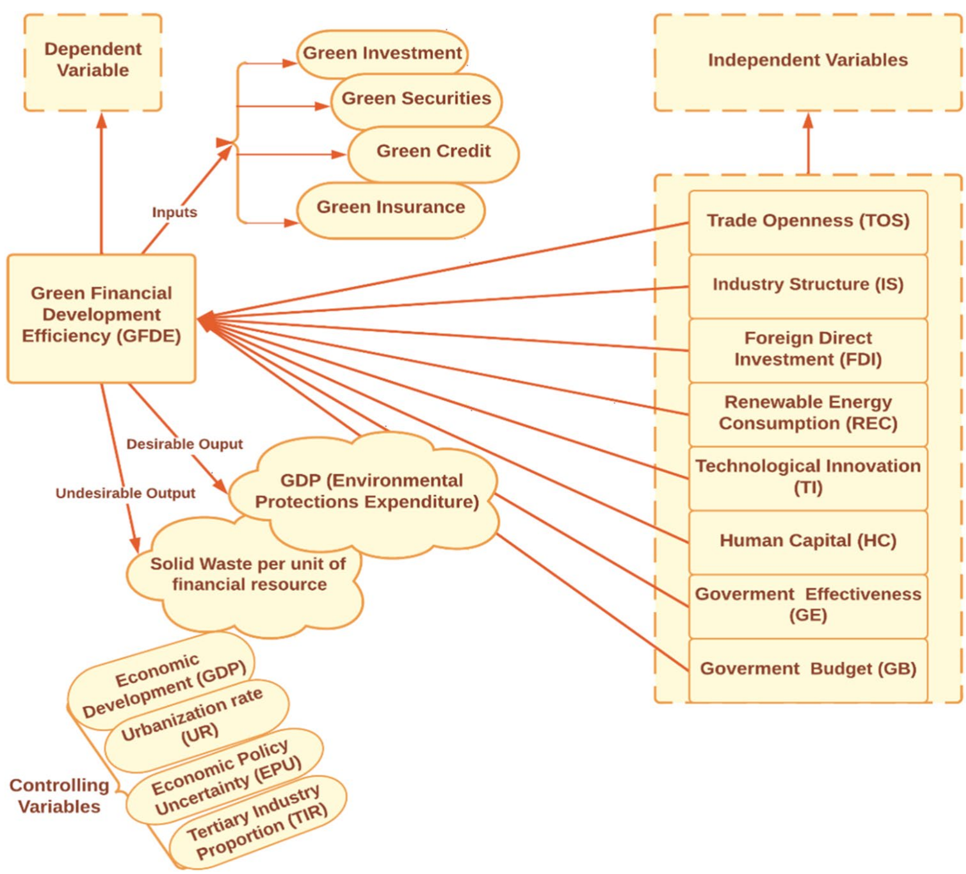


Fig. 2 Theoretical mechanisms of green financial development efficiency

Lv et al. 2021a; Xu et al. 2022b; Gu et al., 2021; Lee and Lee 2022; Liu and Liu 2020). These studies evaluated the green finance development in various regions of China using different methods, including constructing evaluation index systems, conducting empirical analysis using panel data, using entropy value method and DEA-Malmquist index, and using scale directional distance function and common frontier non-radial directional distance function. The results of these studies revealed an overall upward trend in green finance development in China, but there were differences in the level and efficiency of development between regions. However, previous studies did not account for recent years which plays a critical role especially due to major setbacks in 2019 and 2022.

The major challenges facing green finance development in China include imperfect infrastructure, inadequate laws and regulations, and a lack of understanding among financial institutions and businesses. Based on these studies, the scholars made recommendations for improving the level of green finance development in each region. The present study revealed that the green financial development efficiency in the 30 provinces of China can be explained by the index structure developed in this study.

Factors influencing the level of green financial development

In recent years, there has been an increased emphasis on the development of green finance, with scholars and experts from both domestic and international contexts conducting research to examine the current state and factors impacting its growth (Lu et al. 2022; Xu et al. 2022b; Xie et al. 2020; Tang et al. 2022; Musah et al 2022b). Gu et al. (2019) revealed that commercial banks have a strong sense of social responsibility and follow the "equatorial principle" in their green finance operations, while investment banks and other financial institutions have received positive recognition in the industry. The studies revealed that trade openness, industry structure, FDI, innovation, human capital, government budget, and government effectiveness significantly influence green finance.

Financial institutions and SMEs are considered crucial channels for the growth of green finance, as highlighted in studies (Musah et al. 2019; Gu et al. 2021; Lv et al. 2021a, b). However, there is a lack of government support and cooperation in many countries to extend the development of green finance to serve SMEs, hindering the growth of the green economy and finance (Li and Pan 2012). Europe was one of the first regions to implement green financial development, led by Italy, and it requires support from the government for commercial banks and other financial institutions to participate (Falcone et al. 2018). Similarly, despite a good start in China, its late entry into the green finance sector and the presence of obstacles have negatively impacted its growth (Zhou et al. 2022). Yi et al. (2014) found that the infrastructure for green finance in Hubei is not yet perfect and a lack of innovative information asymmetry results in significant financial risks.

Sun and Chen (2022) noted that green finance operations in China are primarily focused on green credit and green insurance and, although it still lags behind some Western developed countries, it holds a bright future. Zhou et al. (2022) acknowledged the challenges in green finance development in China and stressed the value of advanced experiences and measures from some Western developed countries. Wang et al. (2021) provided practical insight into the development of green finance in China, highlighting the current situation and important considerations in the development process and providing policy recommendations.

Studies by Lv et al. (2021a, b) and Xiao et al. (2022) indicate a positive relationship between economic development and the level of green finance development, with carbon emissions and air quality index showing an inverse relationship. Through various methods, including Dagum's Gini coefficient decomposition method, Kernel density estimation, Markov chain, and spatial Markov chain model, the studies analyzed the regional gap and trend of green finance development in China from 2010 to 2019. The results showed an overall upward trend in the index of green finance development in China, although the overall level is still not high and the regional gap is shrinking. The trend of green finance development is also polarized, with high levels initially present in eastern, central, and western China, followed by northeast China.

Zhang et al. (2022b) used coupling coordination degree models, spatial autocorrelation models, and spatial panel models to examine the coordination between green finance and environmental performance in China from 2008 to 2019. The results showed an overall upward trend in the green finance index, with high-value areas primarily located in eastern regions. The literature on green finance in China has explored various aspects, including the policy's impact on industrial transformation, and upgrading. Hence, the need to investigate the determinants of GFDE in China.

Data envelopment analysis (DEA)

Dynamic slack-based measure (DSBM)

In this study, we examine the level of green financial development efficiency in China using panel data from 2010 to 2020. Despite the lack of green financial development indicators in certain regions, such as Tibet, Hong Kong, Macao, and Taiwan, we seek to construct a model for green financial development efficiency. Dynamic data envelopment analysis (DEA) has emerged as a leading methodology for measuring the efficiency of green financial development in reducing environmental pollution and promoting economic growth. This approach has been utilized by several previous studies, both within and outside of China (Luo et al. 2019; Dobos and Vörösmarty 2019; Lv et al. 2021a, b; Aslam et al. 2021; Liu et al 2021; Zhang et al. 2021; Iqbal et al. 2021; Irfan et al. 2022; Shah et al. 2022; Li et al 2022a, b, c). The DEA model evaluates the efficiency of decision-making units (DMUs) using linear mathematical programming (Tone 2010). In this study, the dynamic slack-based measure (SBM) DEA model is used to estimate green financial development efficiency in China. This model, introduced by Tone (2010), is a popular choice among researchers as it provides a comprehensive assessment of the efficiency of DMUs and accounts for changes in efficiency over time (Tone 2021). The dynamic DEA framework is essential for measuring green financial development efficiency as it allows for a thorough evaluation and analysis of changes in efficiency over time. The GFDE of DMUs (provinces) in China is measured using a mathematical formula to estimate the productivity of each DMU (Tone 2010).

$$h_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_r x_{ij}} \tag{1}$$

Assign weight vectors, *u* and *v*, respectively, to inputs and outputs of *green financial development efficiency*. The mathematical formula for calculating *green financial development efficiency* is based upon the constraint that none of the DMUs > 1 based (Sarpong et al. 2022; Wu and Chen 2021; Ma et al. 2017; Zhu et al. 2021). The function of GFDE is estimated as

$$\max\ h_o(u, v) = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_r x_{io}}, \tag{2}$$

$$\text{subject to} \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1, 2 \ldots .., jo, \ldots, n, \text{ (constraints)} \tag{3}$$

$$\begin{cases} u_r \geq 0, r = 1, 2, \ldots .s, \\ u_i \geq 0, i = 1, 2, \ldots .m, \end{cases} \tag{4}$$

In this study, the dynamic slack based measure (DSBM) model is established under the assumption that the data utilized is positive, with *X* and *Y* being greater than zero. The input and output matrices, *X* and *Y*, respectively, are explicitly defined within this study.

$$\begin{cases} X = \left(x_{1,} x_2, \ldots \ldots, x_n\right) \in R^{mxn} \\ Y = (y_1, y_2, \ldots \ldots, y_n) \in R^{sxn} \end{cases} \tag{5}$$

$$\text{DSBM} - [\text{Min}]\rho_o^{\min} = \min_{\lambda, s^-, s^+} \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 - \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^-}{y_{ro}}} \tag{6}$$

$$\text{subject to} \begin{cases} x_{io} = \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^-(i=1, \ldots .m) \\ y_{ro} = \sum_{j=1}^{n} y_{ij}\lambda_j + S_r^+(r=1, \ldots .s) \\ \lambda_j \geq 0(\forall j), s_i^- \geq 0(\forall jr \geq 0(\forall r) \\ \text{DMU}_o = (x_o, y_o) \text{if}\, \rho_o^{\min} = 1 \text{holds} \end{cases} \tag{7}$$

$$\text{DMU}_o = (x_o, y_o) if\, \rho_o^{\min} = 1.$$

The efficiency of the DSBM framework was evaluated based on the presence of zero slack values, both for inputs ($S^- = 0$) and output ($S^{+^*} = 0$) as depicted in Fig. 3. When all input and output slacks are zero, the DSBM framework will be considered efficient.

Index construction of green financial development efficiency

In this study, we used the dynamic slack-based measure (DEA) model to evaluate the efficiency of green financial development in China from 2010 to 2020. The DEA model is a well-established method in the field and has been used in previous studies (Yi et al. 2014; Yu and Xu 2019; Xie et al. 2020; Lv et al. 2021a, b; Zhou et al. 2022) to assess the impact of green investment, green securities, green credit, and green insurance on regional GDP and solid waste per financial resources. This study uses inter-provincial panel data to construct an index for measuring the efficiency of green financial development. Despite the absence of data from some regions like Tibet, Hong Kong, Macao, and Taiwan, the DEA model allows for a thorough assessment and analysis of changes in green financial development efficiency over time. Table 1 briefly describes the index structure of the model.

In this study, the missing data was filled in using linear interpolation and is summarized in Table 2. The descriptive statistics of the input and output variables were also calculated, including the mean, standard deviation, skewness, kurtosis, and Jarque–Bera normality, to provide a comprehensive overview of the data from 2010 to 2020. To achieve the objective of examining regional green financial development efficiency (GFDE) in China, an index system was established. This was done with the aim of contributing to China's green transformation agenda. (All data is summarized in Table 2 and analyzed over the period of 2010 to 2020).

The descriptive statistics, presented in Table 2, provide information on the central tendency and dispersion of the input and output variables used in the study. The mean values of the input variables, green investment, green credit,

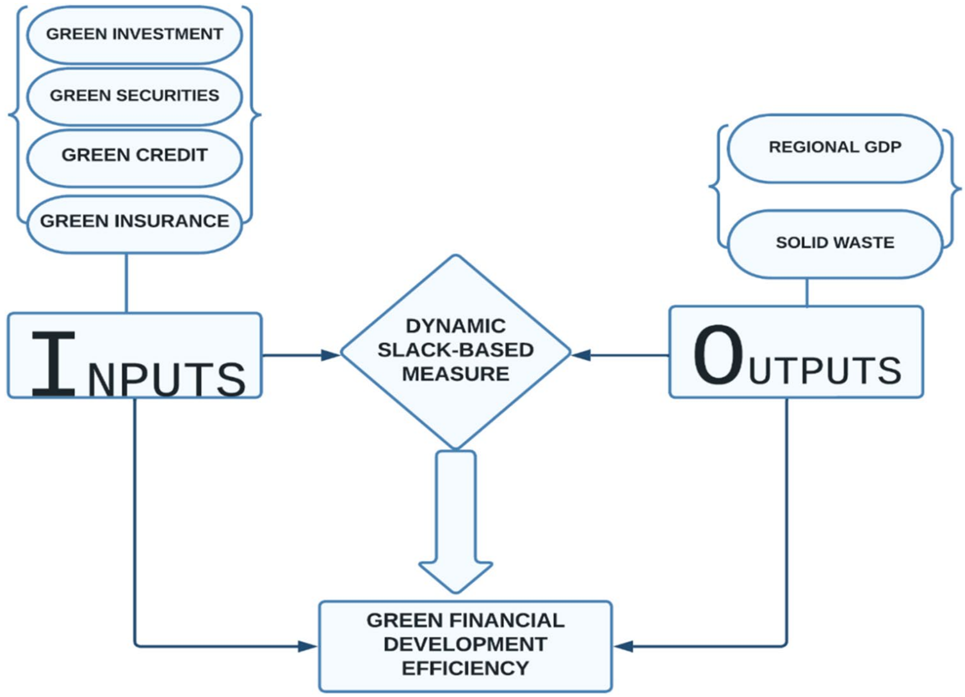


Fig. 3 Estimating green financial development efficiency

Table 1 The index structure of the DSBM DEA model

Type	Variables	Definition	Unit	Behavior of relationship	Source
Inputs	Green investment (GI)	Regional government departments at all levels invest in environmental pollution control/GDP %	%	Positive	China Statistical Yearbook; Wind database
	Green securities (GS)	The proportion of the market value of environmentally conscious companies listed on A-shares compared to the total market value of all companies listed on A-shares	%	Negative	China Statistical Yearbook; Wind database
	Green credit (GC)	Interest expenditure of high energy-consuming enterprises/interest expenditure of industrial industries %	%	Negative	China Statistical Yearbook; Wind database; CSMAR database
	Green insurance (GI)	Agricultural insurance income/property insurance income	%	Positive	China Insurance Statistical Yearbook
Output	Desirable output: regional GDP (GDP)	Gross regional product—environmental protection expenditure	Billion dollars	Positive	China EPS database
	Undesirable output: solid waste per unit of financial resources (SWF)	Solid waste output/(deposit + loan)	Billion dollars	Negative	China Environmental Statistics Yearbook

green security, and green insurance were 28.13, 59.12, 2.56, and 7.79, respectively. The output variables, gross regional product—environmental protection expenditure and solid easte output, had mean values of 62,699.01 and 2.02, respectively. To determine the normality of the data, the Jarque–Bera normality test was performed, which revealed that the data was normally distributed. The results showed that skewness and excess kurtosis values were between (−0.5 to 0.5) and (−2 to 2), respectively. The results of the Jarque–Bera test, as shown in Table 2, indicated that the

Table 2 Descriptive statistics

Index	Variable	Mean	SD	Max	Min	SK	KT	JB	Prob
Inputs	GI	28.13	15.16	100	0.01	0.02	1.23	18.56	0.000*
	GC	59.12	12.60	97.61	26.41	0.06	1.42	14.20	0.000*
	GS	2.56	2.26	7.30	0.07	0.14	0.48	11.52	0.000*
	GI	7.79	7.49	69.54	0.35	0.18	0.93	18.12	0.001*
Outputs	SWF	2.02	2.18	1.48	1.03	0.09	1.49	7.04	0.020*
	GDP	62699.01	15027.10	161082.49	15497.30	0.36	1.22	16.80	0.014*

SW skewness, *KT* kurtosis, *JB* Jarque-Bera

*$p < 0.05$

data for all input and output variables were normally distributed as demonstrated by the significant probability values of the test. In the following section, the results of the green financial development efficiency in the four main regions of China will be presented.

Regional green financial development efficiency measure in China

The study investigated the regional green financial development efficiency of China using the dynamic SBM-DEA model. The dynamic SBM model was adopted to inculcate the dynamic nature of the four regions and 30 provinces in China. While some provinces and regions in China are known to be industrialized, others are also known for advanced and technological practices in essential areas. The use of dynamic SBM ensured that all these factors were considered in building the index structure. Previous studies such as Tang et al (2022) did not consider undesirable output such as industrial waste in computing the green financial development efficiency of China. This limited their study without considering the effect of investment in green financing practices on reducing environmental havoc. Hence, this study adopted the *DSBM-DEA* model since it allowed for the inclusion of undesirable output in estimating efficiency measures. The *DSBM-DEA* model is popularly known for solving the problem of slackness of input and output of green financial development, hence its appropriateness for this study (Sarpong et al. 2022; Wu and Chen 2021; Tone 2021). The main thrust of the study was to investigate whether the regional divisions within China were achieving high green financial development efficiency (DSBM = 1). The closer a region gets to (1) revealed a higher green finance efficiency level (Tone and Tsutsui 2014; Tone 2021). Table 3 presents the report of the DSBM on regional green financial development efficiency by proving a deep understanding of the trajectories of regional green finance development efficiency in China.

Overall, China has a good green financial development efficiency (GFDE = 0.7867). This implies that China's contribution to sustainable development through green financial activities is progressive. The country is doing its best despite not achieving optimum production activities and investment practices aimed toward the total alleviation of non-green investment practices. In 2010, the GFDE of China within the 30 provinces involved in the study was (0.7845) which rose to (0.8161) by 2014. This revealed a significant 4.02% increase in green financial development efficiency. The study found a significant drop of 4.73% by 2020 (0.7687). Figure 4 illustrates the nationwide GFDE of China geared towards promoting green transformation in China.

A central issue is that the majority of provinces known for their industrial and economic activities such as Tianjin (0.9729), Jiangsu (0.9631), Anhui, Shandong (09515), and Shanghai (0.9443) acquired higher GFDE. The loss to sustainable productivity was below 6%. Less than 10 provinces in China experience a loss of 40% or below towards sustainable development through financial activities. China's sustainable practices through their green credit, investment, securities, and insurance appear to be doing relatively well despite the setbacks from provinces such as Yunnan, Shanxi, Shaanxi, Sichuan, and Liaoning as shown in Table 3.

Table 3 shows the results of the analysis of green financial development efficiency (GFDE) across different regions of China. The data revealed that the green finance sector in China has experienced a slow growth trend from 2010 to 2020. The GFDE analysis shows that there is an imbalance in the level of green finance development across regions in China, with some regions showing higher levels of green finance development than others. The imbalanced development can be attributed to differences in investment levels and support for green finance across regions and sectors in China.

Since the main focus of the study was to investigate the regional GFDE of China, the study further analyzed the data taking into consideration the four main regional divisions. Equally important, the study found that the Eastern region of China had the highest GFDE of 0.8732 followed by the Central, Northeast, and Western sector with respective GFDEs of 0.8026, 0.7185, and 0.7179. Admittedly, it is

Table 3 Regional green financial development efficiency in China

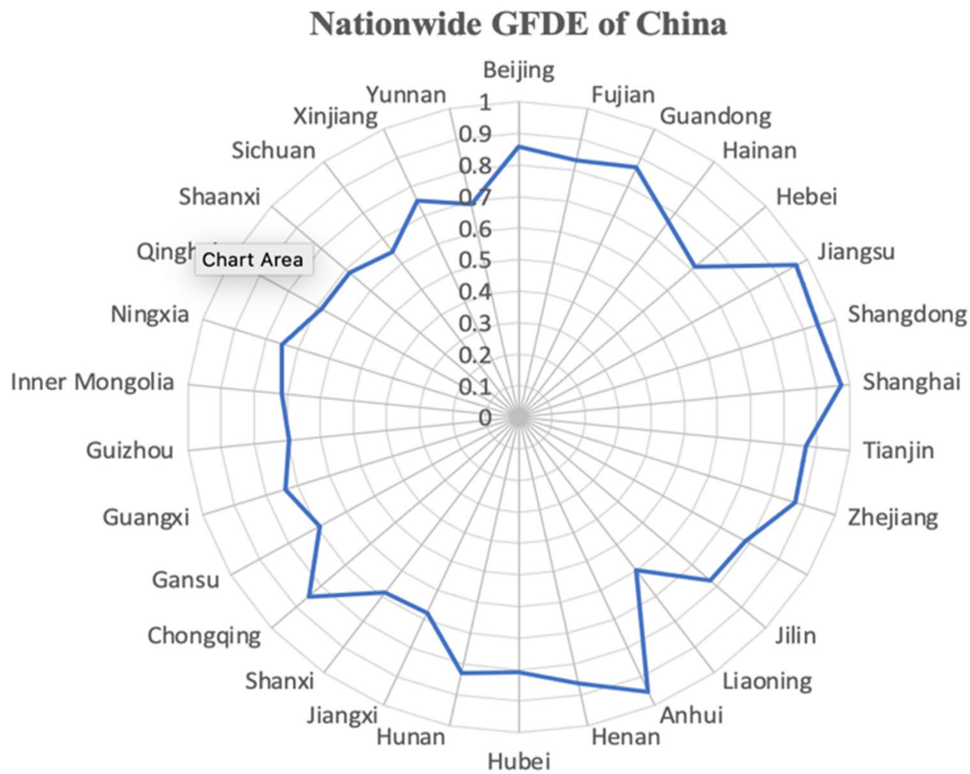
Provinces	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean	Rank
Eastern sector													
Beijing	0.7909	0.7804	0.8817	0.9396	0.9201	0.8267	0.8774	0.8215	0.8307	0.9074	0.8515	0.8571	9
Fujian	0.8668	0.7658	0.9290	0.9036	0.9274	0.8373	0.7874	0.7369	0.8179	0.8174	0.7669	0.8324	11
Guangdong	0.8588	0.8252	0.8616	0.8472	0.8715	0.8990	0.8767	0.8494	0.8695	0.9067	0.8794	0.8677	7
Hainan	0.9195	0.6329	0.7759	0.8226	0.6638	0.7884	0.8217	0.6687	0.7597	0.8517	0.6987	0.7640	16
Hebei	0.7393	0.6167	0.6036	0.6424	0.6474	0.7490	0.7420	0.7641	0.7692	0.7720	0.7941	0.7127	21
Jiangsu	0.9672	0.9614	0.9414	0.9849	0.9755	0.9559	0.9295	0.9474	0.9674	0.9859	0.9774	0.9631	2
Shandong	0.9381	0.9340	0.9775	0.9741	0.986	0.9903	0.9217	0.8804	0.9087	1.0203	0.9104	0.9492	4
Shanghai	0.9688	0.9648	0.9454	0.9344	0.9233	0.9348	0.9307	0.923	0.9447	0.9648	0.953	0.9443	5
Tianjin	0.9353	0.9535	0.9771	0.9883	0.991	0.9938	0.9701	0.9385	0.9621	1.0238	0.9685	0.9729	1
Zhejiang	0.8213	0.8101	0.8362	0.8596	0.8791	0.8822	0.8666	0.8808	0.8933	0.9122	0.9108	0.8684	6
Mean	0.8806	0.8245	0.8729	0.8897	0.8785	0.8857	0.8724	0.8411	0.8723	0.9162	0.8711	**0.8732**	
Northeast sector													
Heilongjiang	0.8980	0.7934	0.853	0.8286	0.7882	0.7473	0.7587	0.6451	0.7364	0.7767	0.8072	0.7848	14
Jilin	0.7944	0.7368	0.8004	0.9049	0.8429	0.7214	0.7291	0.6363	0.7168	0.7471	0.8619	0.7721	15
Liaoning	0.5913	0.5583	0.6136	0.6163	0.5722	0.5335	0.6051	0.6229	0.6554	0.6231	0.5912	0.5986	30
Mean	0.7618	0.6962	0.7557	0.7833	0.7344	0.6674	0.6976	0.6348	0.7029	0.7156	0.7534	**0.7185**	
Central sector													
Anhui	0.9671	0.9314	0.9517	0.9614	0.9451	0.9512	0.9093	0.9538	0.9653	0.9728	0.9571	0.9515	3
Henan	0.8087	0.8151	0.8708	0.8829	0.8658	0.8721	0.8561	0.8568	0.8766	0.8931	0.8778	0.8614	8
Hubei	0.9043	0.8918	0.8545	0.8387	0.8358	0.7577	0.6672	0.6889	0.8069	0.7787	0.8478	0.8066	13
Hunan	0.9659	0.7691	0.7942	0.7964	0.7903	0.8128	0.8935	0.9591	0.9272	0.8338	0.5781	0.8291	12
Jiangxi	0.6688	0.7518	0.7471	0.7363	0.7412	0.7318	0.5661	0.5647	0.5915	0.7573	0.6194	0.6796	28
Shanxi	0.7014	0.6887	0.7949	0.7489	0.7502	0.6678	0.6074	0.5081	0.5354	0.7699	0.7901	0.6875	25
Mean	0.836	0.808	0.8355	0.8274	0.8214	0.7989	0.7499	0.7552	0.7838	0.8343	0.7784	**0.8026**	
Western sector													
Chongqing	0.8414	0.8458	0.879	0.8944	0.8863	0.8871	0.8362	0.7728	0.8038	0.8262	0.8563	0.8481	10
Gansu	0.5623	0.6435	0.7112	0.7538	0.7031	0.7357	0.7313	0.6837	0.6922	0.6931	0.7057	0.6923	23
Guangxi	0.7546	0.6433	0.7602	0.8074	0.7702	0.7608	0.7862	0.7339	0.7647	0.7239	0.6108	0.7378	19
Guizhou	0.5583	0.6056	0.7148	0.659	0.7527	0.7826	0.7646	0.7424	0.7848	0.6428	0.6278	0.6941	22
Inner Mongolia	0.7381	0.7672	0.6645	0.7185	0.8116	0.7173	0.7185	0.6408	0.6209	0.7421	0.7366	0.716	20
Ningxia	0.7172	0.7572	0.8741	0.9265	0.9736	0.8154	0.7563	0.6578	0.6285	0.6158	0.5105	0.7484	18
Qinghai	0.4998	0.7085	0.7049	0.7043	0.7127	0.6528	0.7082	0.7666	0.7458	0.7372	0.6025	0.6858	27
Shaanxi	0.6041	0.6769	0.7184	0.7473	0.7472	0.7520	0.8545	0.5405	0.5948	0.6052	0.7077	0.6862	26
Sichuan	0.6859	0.6353	0.6325	0.5890	0.6152	0.6258	0.5875	0.6002	0.6537	0.7901	0.6958	0.6465	29
Xinjiang	0.6939	0.7511	0.7377	0.7599	0.8001	0.8183	0.7462	0.7310	0.8030	0.7149	0.7102	0.7515	17
Yunnan	0.7168	0.7322	0.7258	0.7506	0.7249	0.7322	0.7286	0.6242	0.6748	0.6142	0.5702	0.6904	24
Mean	0.6702	0.7061	0.7385	0.7555	0.7725	0.7527	0.7471	0.6813	0.7061	0.7005	0.6667	**0.7179**	

not surprising since most of the provinces with high GFDE were located in the Eastern sector of China. There is more room for improvement for the Northeast and Western sectors since they recorded losses of more than 28% to sustainable development through their financial activities. Details of the performance in GFDE of the four main sectors were further illustrated graphically to give a deep understanding.

It can be seen from the results that during the period 2010–2020, the green financial development efficiency of the Eastern provinces and cities was above 0.71, showing an overall upward trend of 0.8213 to 0.9162. For Tianjin province, it recorded higher GFDE right from 2010 (0.9652) to 2020 (0.9685). Despite the good performance of these regions, provinces such as Hebei performed poorly towards sustainable development with a GFDE score of 0.7393 in 2010 and to upward increment of 0.7941.

The central sector which included provinces such as Anhui, Henan, Hubei, Jiangxi, and Shanxi performed slightly better than the Western and Northeast sectors as

Fig. 4 Overall green financial development efficiency of China



shown in Fig. 5. Anhui province recorded the best GFDE in this sector with a 95.15% improvement in green finance activities and contribute towards sustainable development of China. During the year-by-year comparison, it was revealed that the Central sector experienced a declining GFDE. In 2010, the overall GFDE of this sector was 0.836, which decreased to 0.7989 in 2014 and further reduced to 0.7838 in 2020. Despite the overall improvement in GFDE of 80.26%, the declining state of GFDE is something to be further investigated and resolved.

The study showed that while the eastern and central regions of China showed relatively good green financial development efficiency (GFDE), the northeast region experienced backward GFDE, which was generally lower than that of the other regions. In 2010, the GFDE score for the northeast sector was 76.18%, indicating a loss of 23.82% in the productivity of green financial activities. This region showed volatility in its GFDE, with a drop to 69.62%. The green financial development efficiency in Liaoning, for example, was quite low, decreasing year by year from 2010 to 2014 (0.593 to 0.5335). To address these disparities, the government and relevant stakeholders may consider implementing policies and initiatives to promote sustainable finance across all regions and achieve green transformation in China. The study further investigated the driving forces behind the differences in the development level of green finance among the regions. This has been thoroughly explained in the next sections.

Analysis of influencing factors of green financial development toward sustainable development

This study analyzes how economic, social, and environmental indicators such as trade openness, industry structure, foreign investment, energy consumption, technological innovation, human capital, government effectiveness, and budget influences green financial development efficiency in pursuits of sustainable development in China.

Variable selection

The second phase of this study investigated the determinants of GFDE from 2010 to 2020. The study chose the results from the first phase (estimating GFDE) as the dependent and main explained variable while the explanatory variables (independent variables included trade openness, industry structure, foreign investment, energy consumption, technological innovation, human capital, government effectiveness, and budget). The study further controlled variables such as GDP, urbanization, economic policy uncertainty, and tertiary industry proportion in China. The next paragraphs clearly illustrate the variables in detail:

(a) Dependent variable: green financial development efficiency (GFDE): The study constructs an index struc-

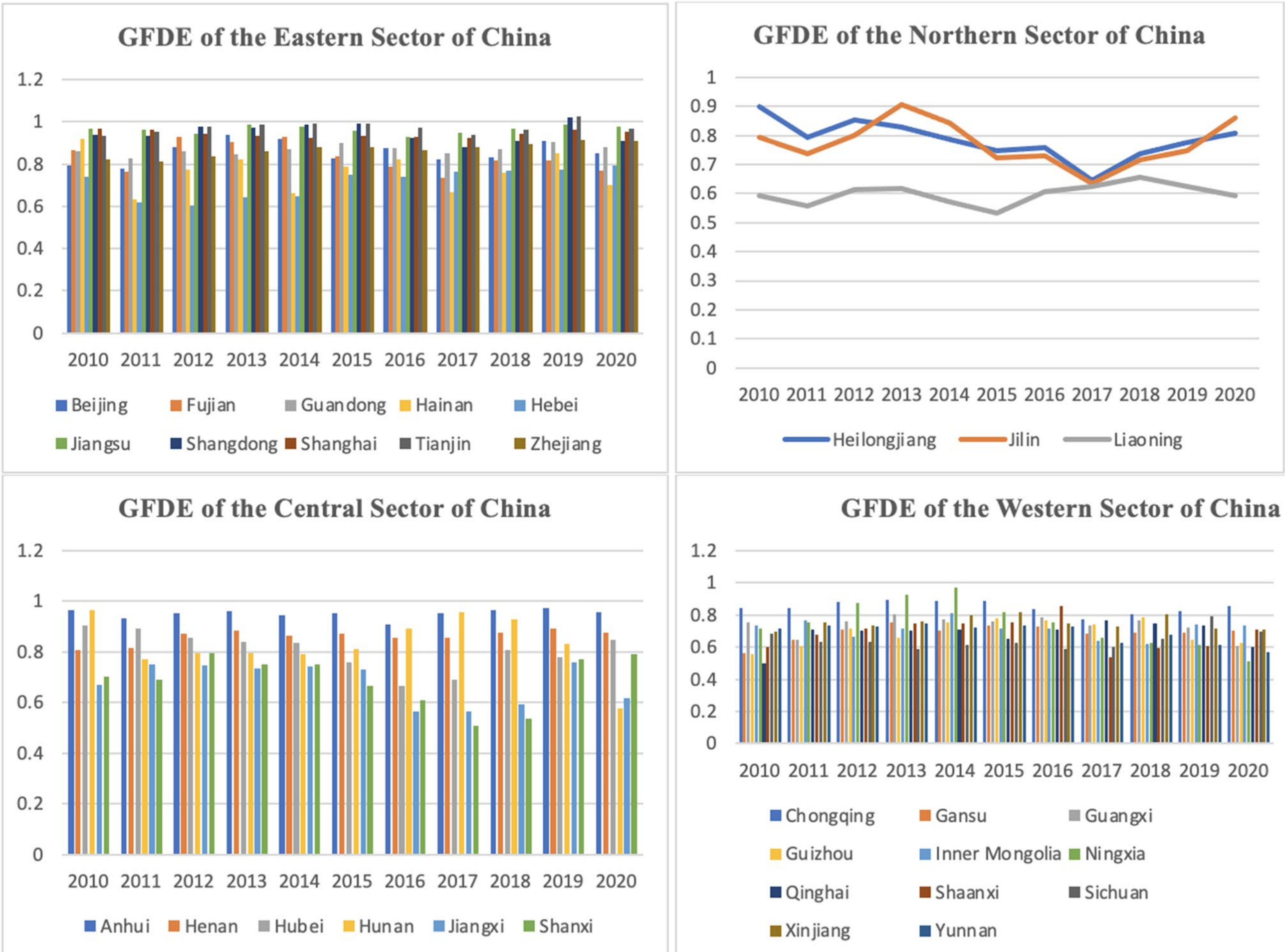


Fig. 5 Green financial development efficiency of China within the Central Region

ture that assessed the trend of the development level of regional green finance using their input and output dimensions. The study compared green credit, green investment, green securities, and green insurance to outputs (desirable: the regional economic development of China as expenditure of environmental protection) and (undesirable output such as solid waste per unit of financial resources).

(b) Independent variables: TOS, IS, FDI, REC, TI, HC, GE, and GB: Green financial development has been affected by several internal and external factors in China. Prior researchers (Fang and Lin 2019; Yu and Xu 2019; Musah et al. 2021a, e; Lv et al. 2021a, b; Musah et al. 2021c; Tao et al. 2022; Xie et al. 2022) considered influencing factors such as trade openness, industry structure, FDI, energy consumption structure, human capital, government effectiveness, and budget of China. These studies revealed that the green financial development of any country significantly can be affected by macro-economic factors as mentioned above. Hence, this study analyses the following explanatory variables as the influencing factors of GFDE in China. To better understand the influencing factors of GFDE, the study controlled some variables to produce a concrete and thorough understanding of the phenomenon under investigation.

(c) Control variables: GDP, UR, EPU, and TIR: In order to better study the extent to which China's regional green finance development is affected by the determinant of green finance, this study incorporates control variables into other factors that affect the level of green financial development to make the research results more convincing (Musah et al. 2020; Chen and Chen 2021; Sarpong et al. 2022). The study further justified the reason for the selection of control variables as shown below;

(i) *Economic development* is a very important influence factor on regional green financial development, expressed in terms of per capita gross regional product. Generally speaking, the more developed a region's economy is, the more resources it can invest in innovation and R&D. The improvement of the technological level will affect the efficiency of input and output, thereby affecting the level of regional green finance development.

(ii) Moreover, *urbanization* is mainly the transfer of many people to cities and towns, which may have a certain impact on regional green finance development. This study expresses it with the proportion of the urban population in the total population. With the comprehensive implementation of China's new urbanization strategy, the continuous advancement of employment structure and urbanization changes are quietly occurring in the process, which will inevitably affect the industrial structure. Urbanization increases the urban population by transferring surplus rural labor to cities and towns.

(iii) *Economic policy uncertainty* is considered a risk in which government policies and regulatory frameworks are undefined for the near future. This phenomenon may lead businesses and individuals to delay spending and investments because of uncertainty in the market. The higher level of economic and policy uncertainty can decrease new green investments, and this will slow down the transformation to a green economy and sustainable development.

(iv) *The level of tertiary industry proportion* directly affects pollution emissions and environmental governance and therefore has an important impact on green finance development, expressed as the ratio of tertiary industry-added value to GDP. This has been presented in Table 4.

Model construction

The study employed the generalized moment of methods for analyzing the panel data collected. This involves employing robust econometric models that aim to thoroughly explain the determinants of *GFDE* in China between the period of 2010 and 2020. The study started by building an initial model which sought to explore how determinants such as trade openness, industry structure, foreign direct investment, energy consumption, technological innovation, human capital, government effectiveness, and budget influences dependent variable (green financial development efficiency) in China. In mathematical representation, it can be equated as

$$GFDE = f(TOS, IS, FDI, REC, TI, HC, GC, GB) \tag{8}$$

The equation is transformed into logarithms;

$$lnY_{i,t} = \beta_0 + \beta_1 lnX1_{i,t} + ln\beta_2 X2_{i,t} + \beta_3 lnX3_{i,t} \ldots .. + \beta_n lnXn_{i,t} + \mathcal{E}_{i,t} \tag{9}$$

The study decomposed independent variables (X_1, X_2,… X_n) into TOS, IS, FDI, REC, TI, HC, GE, and GB, to predict the outcome of the GFDE. The next equation presents the model as

$$\text{lnGFDE}_{i,t} = \beta_0 + \beta_1\text{lnTOS}_{i,t} + \beta_2\text{lnIS}_{i,t} + \beta_3\text{lnFDI}_{i,t} + \beta_4\text{lnREC}_{i,t} + \beta_5\text{lnTI}_{i,t} + \beta_6\text{lnHC}_{i,t} + \beta_7\text{lnGC}_{i,t} + \beta_8\text{lnGB}_{i,t} + \mathcal{E}_{i,t} \tag{10}$$

This study utilized a regression model consistent with prior research, assuming linear relationships between the dependent variables, independent variables, and controls. The model aimed to test the stated hypotheses and establish the relationship between these variables. This approach is expected to provide valuable insights and contribute to the advancement of knowledge in the field.

$$\text{lnGFDE}_{i,t} = \beta_0 + \beta_1\text{lnTOS}_{i,t} + \beta_2\text{lnIS}_{i,t} + \beta_3\text{lnFDI}_{i,t} + \beta_4\text{lnREC}_{i,t} + \beta_5\text{lnTI}_{i,t} + \beta_6\text{lnHC}_{i,t} + \beta_7\text{lnGC}_{i,t} + \beta_8\text{lnGB}_{i,t} + \textstyle\sum_{i=1}^{n} \beta\text{Controls}_{it} + \mathcal{E}_{i,t} \tag{11}$$

$$\text{lnGFDE}_{i,t} = \beta_0 + \beta_1\text{lnTOS}_{i,t} + \beta_2\text{lnIS}_{i,t} + \beta_3\text{lnFDI}_{i,t} + \beta_4\text{lnREC}_{i,t} + \beta_5\text{lnTI}_{i,t} + \beta_6\text{lnHC}_{i,t} + \beta_7\text{lnGC}_{i,t} + \beta_8\text{lnGB}_{i,t} + \beta_9\text{lnGDP}\left(\text{C}_1\right) + \beta_{10}\text{lnUR(C\_2)}_{i,t} + \beta_{11}\text{lnEPU(C\_3)}_{i,t} + \beta_{12}\text{lnTIR(C\_4)}_{i,t} + \mathcal{E}_{i,t} \tag{12}$$

where β_0 is the intercept, β_1, β_2, β_3, β_4, β_5, β_5, … β_8 is the coefficient of explanatory variables, TOS, IS, FDI, REC, TI, HC, GC, and GB, respectively, i is the index of provinces (DMUs) ($i = 1, 2 \ldots, 30$), and t represents the year ($t = 1, 2, 3, 4, 5, 6, 7, 8, 9, 10$), ε is the error. For the controls, it represents the variables that were controlled such as lnGDP, lnUR, lnEPU, and lnTIR.

Econometric estimation

The study adopted five main diagnostic approaches to analyze the econometric models. This includes initial data standardization, multicollinearity, autocorrelation, cross-sectional dependency tests, slope homogeneity test, unit root test, and co-integration tests as shown in Fig. 6.

Pre-estimation

The study starts by first standardizing the data collected for the study. The study adopted several economic indicators which come with different metric scales and quantitative levels. This allowed researchers to eliminate inherent predictive quantitative relationships among the variables

Table 4 Variable definition

Acronym	Variable name	Definition	Predictive behavior	Source
Dependent variable				
GFDE (Y)	Green financial development efficiency	The index system is constructed output/input dimensions of green finance as given by the DSBM	Positive	Authors own construct
Independent variable				
TOS (X1)	Tertiary openness	Total import and export/GDP	Positive	China Statistical Yearbook (2010–2020)
IS (X2)	Industry structure	Industrial-added value/GDP	Positive	China Statistical Yearbook (2010–2020)
FDI (X3)	Foreign direct investment	Profits, equity capital, reinvestment earnings, and other major capital affect the economy	Positive	China Statistical Yearbook (2010–2020)
REC (X4)	Renewable energy consumption	The proportion of coal consumption in energy consumption	Negative	China Energy Statistics Yearbook (2010–2020); China Statistical Yearbook (2010–2020)
TI (X5)	Technological innovation	Number of green patent applications	Positive	China Statistical Yearbook (2006–2020); Wind Database
HC (X6)	Human capital	Utilizable skills, knowledge, and experience of a person or group that may be applied to the economy	Positive	China Statistical Yearbook (2006–2020)
GE (X7)	Government effectiveness	A measure of the quality of governance on a numerical scale ranging from −2.5 (weak) to 2.5 (strong)	Positive	China Statistical Yearbook (2010–2020)
GB (X8)	Government budget	The state's process of redistribution and rational use of fiscal revenue	Positive	China Statistical Yearbook (2010–2020)
Control variables				
GDP (C_1)	Economic development	GDP/population (yuan/person)	Positive	China Statistical Yearbook (2010–2020)
UR (C_2)	Urbanization rate	The number of long-term city residents	Negative	China Statistical Yearbook (2010–2020)
EPU (C_3)	Economic policy uncertainty	This is the index of economic policy uncertainty	Negative	Economic Policy Uncertainty database (2010–2020)
TIR (C_4)	Tertiary industry proportion	The ratio of tertiary to secondary industry-added value (%)	Positive	China Statistical Yearbook (2010–2020)

which may influence the results of this study. This gives the model the chance for larger intervals that allow for comparison and interpretation of the different variables. The standardization was conducted during the data cleaning stage in Excel. All the data were transformed using the logarithm function (see Eq. 9).

Cross-sectional dependency tests China has a large economy with a population of more than 1.4 billion with 34 provinces with different economic representation. The study performed a cross-sectional dependency test using the data from the 30 provinces. Looking at the population and number of decision-making units (provinces) involved in this study, it can be assumed and anticipated the presence of cross-dependence among the 30 provinces. Failure to conduct this test could cause data series to be biased and spurious causing misleading findings (Bashir et al. 2020; Pesaran 2021; Sinha et al. 2022). Hence, the researcher saw the need to conduct this pre-diagnostic test using the Breusch and Pagan (1980) Lagrange multiplier test, Pesaran (2007) scaled LM test, Friedman (1937) test, and Pesaran (2015) CD test, given in equation as follows;

$$\mathrm{LM} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^{2} \rightarrow \chi^{2}\frac{N(N-1)}{2} \tag{13}$$

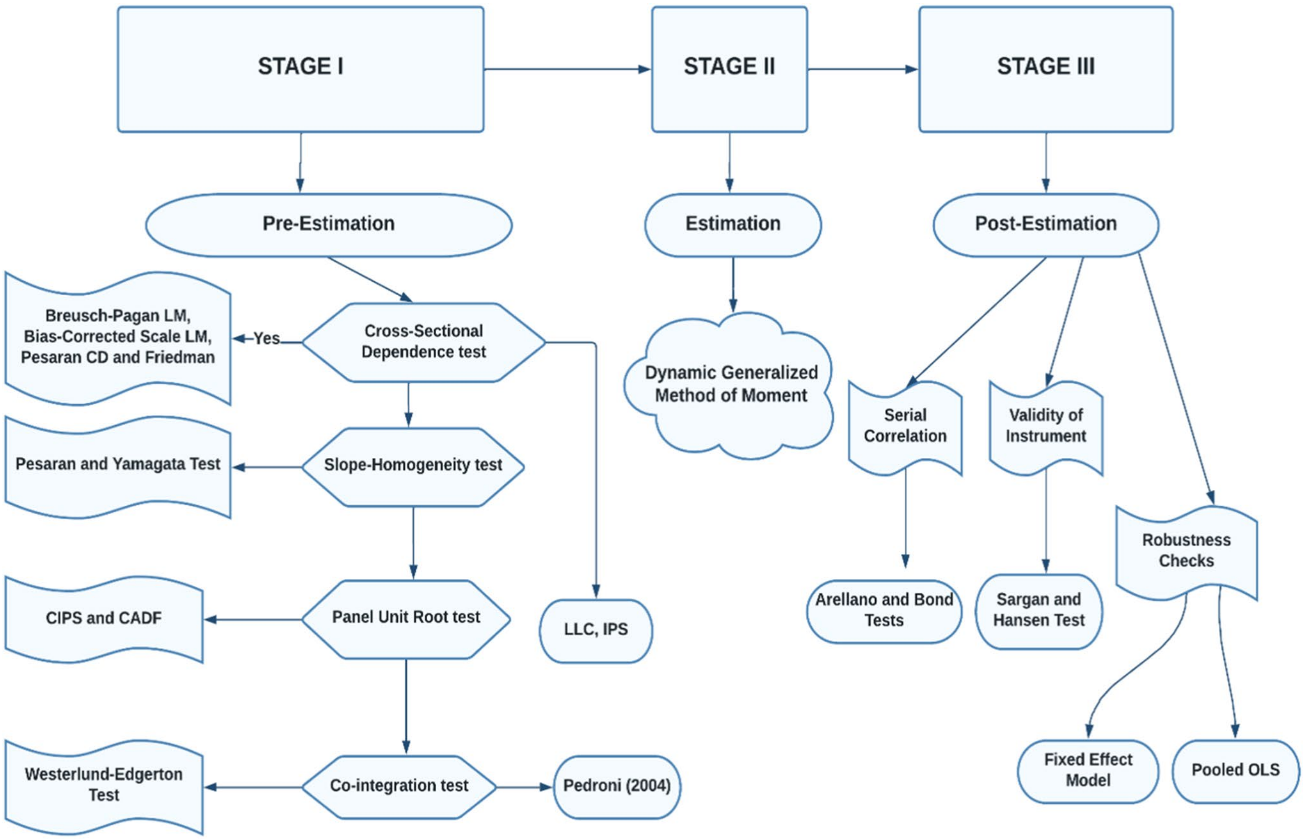


Fig. 6 Estimation strategies adopted for this study

where $\widehat{\rho}_{ij}^2$ is the correlation estimates residuals and χ^2 reports the asymptotical transmission for the time interval (T) (Breusch and Pagan 1980). Due to the limitation of LM in handling N extensive framework. The study further adopted the Pesaran (2015) CD test as shown

$$LM = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T_{ij}\widehat{\rho}_{ij}^2 - 1 \right) \rightarrow N(0,1) \tag{14}$$

This allowed both $T_{ij} \rightarrow \infty$ and $N \rightarrow \infty$. The study estimated the cross-sectional dependence of the decision unit on the assumption that there is no cross-sectional dependence among the units as shown in the equation as

$$CD_\rho = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\widehat{\rho}_{ij}^2 \rightarrow N(0,1) \tag{15}$$

Slope homogeneity The study further tested the existence of heterogeneity in the slopes of the panel data. This was done after establishing that there was no presence of cross-sectional dependency in the decision-making units. Recent studies such as Khan et al. (2022) emphasized the importance of conducting slope homogeneity tests. Failure of researchers to ignore such pre-estimation could affect the integration order of the variables and biases in results. The study employed the Pesaran and Yamagata (2008) slope homogeneity test. This test was based on a strategy based on ascertaining the delta ($\tilde{\Delta}$) and the adjusted delta ($\tilde{\Delta}_{adj}$) as seen in Eqs. 16 and 17.

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - K}{\sqrt{2K}} \right) \tag{16}$$

$$\tilde{\Delta}_{\text{adj}} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{Z}_{iT})}{\sqrt{\text{var}(\tilde{Z}_{iT})}} \right) \tag{17}$$

Unit root tests The pre-estimation tests used in this study were the Pesaran (2007) CADF and CIPS panel unit root tests. Recent studies (Yunzhao 2022; Büşra 2022; Jamil et al. 2022) have emphasized the importance of panel unit root tests in ensuring the validity of panel regression analysis. Conventional second-generation unit root tests, such as CADF and CIPS, were adopted over first-generation tests (such as LLC and IPS) due to their ability to account for cross-sectional dependence and slope homogeneity (Musah et al 2021c).

The CADF test allows researchers to remove the influence of cross-sectional dependency among the 30 provinces involved in the study (Nosheen and Khan 2022; Chen et al. 2022a, b; Ahakwa 2023). By performing these pre-estimation tests, the researchers aimed to provide robust and reliable results that contribute to the advancement of knowledge in the field. The main aim of this test is to determine whether the series is stationary or not. In a situation where research variables are non-stationary at level (X_t), the study considers the series of first differences (ΔX_t). Pesaran (2007) developed the CIPS test by extending conventional augmented Dickey-Fuller. The CADF is based on this equation:

$$\Delta X_{it} = a_{it} + \beta_i X_{it-1} + \rho_i T + \sum_{j=1}^{n} \theta_{ij} \Delta X_{i,t-j} + \varepsilon_{it} \tag{18}$$

where $_{it}$ denotes the error term, Δ illustrates the differential, and X_{it} is the investigating variables. CIPS is centered on CADF statistics and is described as

$$\mathrm{CIPS} = N^{-1} \sum_{i=1}^{N} \mathrm{CADF}_i \tag{19}$$

Panel co-integration tests After estimating the stationarity of the research variables and correcting them using CIPS and CADF, the study conducted a co-integration test of the error terms before going ahead with the forecasting model. The study employed a cross-sectional Westerlund and Edgerton's (2007) co-integration test to ascertain the long-run spatial dependence of the research variables. The use of the co-integration test accommodated the individual-specific and short-run dynamics in terms of specific constraints, trends, and slope parameters (Ansari 2022; Ahakwa et al. 2023). To ensure the robustness of the co-integration, the study further adopted Pedroni's (2004) co-integration to determine the presence of co-integration or not among the chosen dimensions of variables for constructed models. The use of the Pedroni co-integration test allowed for panel-specific co-integrating vectors. The test uses an error-correction model (ECM) in correcting for the presence of co-integration in error terms. The following equation guided the tests:

$$X_{it} = Y_{it} + \delta_t t + \beta_{it} Z_{it} + \varepsilon_{it} \tag{20}$$

Here, X acts as a regressor and dependent variable while Z becomes explanatory.

Estimations: system generalized method of moment (sGMM)

The current study adopted the system generalized method of moment (sGMM) approach, as presented by Hansen (1982), for the econometric analysis of the research. This choice was made due to the sGMM's capability to instrument both dependent variables and endogenous explanatory factors using "internal" instruments, such as lagged levels and lagged differences. This approach is particularly useful for studies on life satisfaction, which often lack valid "external" instruments. Additionally, sGMM estimation enables the detection of time-invariant variables through the estimation of models in both levels and differences, thus permitting the estimation of effects (Awadhi et al. 2022; Omri et al. 2022; Sun et al. 2022).

The study employed the system GMM estimator (Arellano and Bover 1995) for its efficiency in large datasets and ability to use more instruments than the difference GMM (Roodman 2009a). This approach reduces panel gaps and preserves fixed effects, unlike the difference GMM (Roodman 2009a). The study also adopted the Windmeijer correction and a lag limit of 2 to address heteroskedasticity and autocorrelation (Asongu and Nwachukwu 2017; Roodman 2009b). The endogenous variables included trade openness, industrial structure, FDI, renewable energy consumption, human capital, government effectiveness, and budget. The interdependence and correlation coefficient between the two key components, error terms, and endogeneity variables were also estimated to eliminate simultaneous and endogenous biases. The system GMM estimator was favored in this research due to its ability to handle cross-country effects in the estimation process and control potential endogeneity from the inclusion of explanatory variables. This leads to more reliable and consistent estimates. The panel system GMM estimators used in the study are detailed in the equation:

$$g(\beta) = \Sigma_{i=1}^{M} g(\beta) = \Sigma_{i=1}^{M} Z_i^{'} \varepsilon_i (\beta) \tag{21}$$

where Z_i acts as ($T_i \times p$ instrument cross-sectional matrix i) and $\varepsilon_i (\beta) = (Y_i - f(X_{it}, \beta)$.

Econometric estimations

The study aimed at investigating the role played by economic, social, environmental, and government indicators on green financial development efficiency in China from the period of 2010 to 2020. The study first standardized the raw data collected. Tables 5, 6, 7, 8, and 9 report the prediagnostic econometric estimation as shown below.

Autocorrelation and multicollinearity The study tested for the presence of multicollinearity using VIF and tolerance and the correlation matrix. The study further tested for serial correlation in the panel dataset using the Durbin-Watson value as shown in Table 5.

In the study, Table 5 presents the results of the analysis of the relationship between the dependent variable (GFDE), the eight independent variables (lnTOS, lnIS, lnFDI, lnREC, lnTI, lnHC, lnGE, lnGB), and control variables (lnGDP, lnUR, lnEPU, lnTIR), and Pearson product

Table 5 Autocorrelation and multicollinearity analysis

lnGFDE	1	2	3	4	5	6	7	8	9	10	11	12
lnTOS	1											
lnIS	0.698***	1										
lnFDI	0.459***	0.579***	1									
lnREC	0.592**	0.329***	0.318***	1								
lnTI	0.088***	0.218***	0.582***	0.521***	1							
lnHC	0.581***	0.321***	0.392***	0.138***	0.319***	1						
lnGE	0.632***	0.391***	0.310***	0.126***	0.404***	0.611***	1					
lnGB	0.639***	0.331***	0.316***	0.302***	0.275***	0.591***	0.431***	1				
lnGDP	0.040***	0.202***	0.107***	0.128***	0.108***	0.209***	0.312***	0.357	1			
lnUR	0.108***	0.307***	0.042***	0.112***	0.083***	0.310***	0.484***	0.314***	0.318***	1		
lnEPU	−0.482**	0.239***	0.102***	0.282***	0.073***	0.023**	0.698***	0.381***	0.239***	0.328***	1	
lnTIR	0.378***	0.271***	0.049***	0.037***	0.0023***	0.078***	0.384***	0.278***	0.349***	0.139***	0.129***	1
VIF	1.789	1.902	1.890	2.951	1.028	1.089	2.219	1.853	1.379	1.283	1.872	1.568
Tolerance	0.783	0.439	0.319	0.749	0.639	0.328	0.579	0.329	0.432	0.759	0.410	0.483
Durbin-Watson	2.592											

*, **, and *** signify 1%, 5%, and 10% significance levels, respectively

correlation coefficients are used to measure the linear relationship between the variables, with a value ranging from −1 to 1. Results show both positive and negative correlations among the independent variables, indicating the possibility of multicollinearity. To address this, the study employed the variance inflation factor (VIF) and tolerance values, with VIF values less than 5 and tolerance values greater than 0.2, implying unique impacts of each independent variable on the response variable.

Cross-dependency sectional dependency tests The Breusch-Pagan test (Breusch and Pagan 1980) is widely used to test for heteroscedasticity in econometric models. The Pesaran CD test (Pesaran et al. 1999; Pesaran 2007; Mensa et al. 2021) is a commonly used test to detect cross-sectional dependence in panel data models and has been applied in several studies to examine the relationship between different variables, including financial development, economic growth, and environmental quality. The bias-correlation scaled LM test (Arellano and Bond 1991; Blundell and Bond 1998; Hsiao 2003) is a recently developed test to detect cross-sectional dependence in panel data models and has been used in several studies to examine the relationship between different variables, including economic growth, financial development, and institutional quality. The Friedman test (Friedman 1937; Arellano and Bond 1991; Blundell and Bond 1998) is a non-parametric test that is used to assess the existence of cross-sectional dependence in panel data models and has been used in several studies to examine the relationship between financial development, economic growth, and trade openness.

The results of the cross-sectional dependency tests are presented in Table 6 and show that all of the variables are cross-sectionally dependent, as indicated by the highly significant probabilities (less than 0.1%) in all tests (Friedman 1937; Breusch and Pagan 1980; Arellano and Bond 1991; Blundell and Bond 1998; Pesaran et al. 1999; Hsiao 2003; Pesaran 2007).

Slope homogeneity Table 7 presents the results of the existence of heterogeneity in the slopes of the panel data using the Pesaran and Yamagata homogeneity test (Pesaran and Yamagata 2008). The two test statistics, delta tilde ($\tilde{\Delta}$) and adjusted delta tilde ($\tilde{\Delta}adj$), are used to test for cross-sectional dependence among the residuals of the model. The null hypothesis of the test is that there is no cross-sectional dependence when testing the slope homogeneity among the residuals, while the alternative hypothesis is that there is cross-sectional dependence among the residuals (Pesaran and Yamagata 2008).

In this case, the test results show that the value of the delta tilde (28.098) and adjusted delta tilde (34.781) are both significant at the 1% level, as indicated by the probability

Table 6 Cross-sectional dependency tests

	Breusch–Pagan LM		Pesaran CD		Bias-correlation scaled LM		Friedman test	
	Statistic	Prob	Statistic	Prob	Statistic	Prob	Statistic	Prob
lnGFDE	1958.52***	0.001	196.21***	0.00	28.420***	0.001	31.35***	0.001
lnTOS	2189.31***	0.000	228.14***	0.000	57.48***	0.000	43.69***	0.000
lnIS	4022.14***	0.000	416.79***	0.000	34.39***	0.000	62.93***	0.000
lnFDI	2901.93***	0.000	349.30***	0.000	58.39***	0.000	29.78***	0.000
lnREC	1018.40***	0.000	312.41***	0.000	82.10***	0.000	13.603***	0.000
lnTI	1321.59***	0.000	98.17***	0.000	39.03***	0.000	23.02***	0.000
lnHC	1912.11***	0.000	68.29***	0.000	18.65***	0.000	59.03***	0.000
lnGE	1032.41***	0.000	98.22***	0.000	21.08***	0.000	31.29***	0.000
lnGB	1943.058***	0.000	53.41***	0.000	42.14***	0.000	40.98***	0.064
lnGDP	2016.08***	0.000	94.50***	0.000	9.04***	0.000	47.294***	0.000
lnUR	1025.10***	0.000	84.37***	0.000	13.04***	0.000	59.13***	0.000
lnEPU	2.329.89***	0.000	79.38***	0.000	21.87***	0.000	36.79***	0.000
lnTIR	1084.82***	0.000	39.49***	0.000	38.803***	0.000	29.55***	0.007

*, **, and *** signify 1%, 5%, and 10% significance levels, respectively

Table 7 Pesaran-Yamagata homogeneity test results

Test type	Value	Prob
Delta tilde ($\tilde{\Delta}$)	28.098	0.000***
Adjusted delta tilde ($\tilde{\Delta}_{adj}$)	34.781	0.001***

*** denotes significance at 1% level

values ($p < 0.005$) (Pesaran and Yamagata 2008). This means that the null hypothesis of no slope homogeneity can be rejected and that there is evidence of cross-sectional dependence among the residuals of the model.

These results suggest that the relationship between the independent and dependent variables in the model is influenced by cross-sectional dependencies among the residuals (Pesaran and Yamagata 2008). This highlights the importance of considering the presence of cross-sectional dependence in empirical studies and the potential consequences of ignoring this phenomenon when interpreting the results of such studies (Pesaran and Yamagata 2008).

Unit root test Due to presence of cross-sectional dependency, the second-generation root test was adopted to test the presence of stationarity in the data set. The results of the second-generation unit root test on the set of variables under investigation are reported in Table 8. The test, conducted using CIPS and CADF, is a method used to determine the stationarity of a time series (Sarkodie and Owusu 2020).

Table 8 Second-generation unit root test

Variables	CIPS				CADF			
	Level	Decision	First diff	Decision	Level	Decision	First diff	Decision
lnGFDE	−1.316	I(0)	−3.124***	I(1)	−2.524	I(0)	−2.105**	I(1)
lnTOS	−1.019	I(0)	−3.212**	I(1)	−2.988	I(0)	−3.051**	I(1)
lnIS	−1.039	I(0)	−2.910***	I(1)	−1.962	I(0)	−3.938***	I(1)
lnFDI	−2.802	I(0)	−1.156***	I(1)	−2.097	I(0)	−3.012**	I(1)
lnREC	−3.429	I(0)	−2.224**	I(1)	−2.891	I(0)	−3.013***	I(1)
lnTI	−1.603	I(0)	−1.722**	I(1)	−3.081	I(0)	−2.187**	I(1)
lnHC	−2.089	I(0)	−3.668*	I(1)	−3.755	I(0)	−3.514***	I(1)
lnGE	−1.467	I(0)	−3.189**	I(1)	−3.297	I(0)	−3.819**	I(1)
lnGB	−1.893	I(0)	−1.624**	I(1)	−3.282	I(0)	−3.283***	I(1)
lnGDP	−1.782	I(0)	−3.107***	I(1)	−2.527	I(0)	−4.228**	I(1)
lnUR	−2.439	I(0)	−3.219***	I(1)	−2.101	I(0)	−2.186***	I(1)
lnEPU	−1.384	I(0)	−2.951**	I(1)	−3.429	I(0)	−3.545**	I(1)
lnTIR	−1.083	I(0)	−2.087**	I(1)	−3.203	I(0)	−2.392***	I(1)

*, **, and *** signify 1%, 5%, and 10% significance levels, respectively

Table 9 Panel co-integration analysis

Panel co-integration test	*t* statistics	Prob
Pedroni's (2004) co-integration analysis		
Panel modified Phillips-Perron statistics	2.8978***	0.000
Panel Phillips-Perron statistics	−8.2973***	0.000
Panel ADF statistic	−1.8932***	0.000
Kao's (1999) co-integration		
Modified Dickey-Fuller *t* statistic	−2.970***	0.000
Dickey-Fuller *t* statistic	−3.892***	0.000
Augmented Dickey-Fuller *t* statistic	−2.879***	0.000
Unadjusted, modified Dickey-Fuller *t* statistic	−3.782***	0.000
Westerlund's Edgerton's (2007) co-integration		
Variance ratio	−3.289***	0.000

*, **, and *** signify 1%, 5%, and 10% significance levels, respectively

The test results are reported for both the level and first difference of each variable. If a time series is non-stationary at level, the first difference of the series can sometimes make it stationary (Hussain et al. 2022).

The variables under investigation include lnGFDE, lnTOS, lnIS, lnFDI, lnREC, lnTI, lnHC, lnGC, lnGB, lnGDP, lnUR, lnEPU, and lnTIR. The decision of the unit root test, indicated by "I(0)" for stationary series and "I(1)" for non-stationary series after first differences, is based on the hypothesis testing framework, with the null hypothesis being non-stationarity (unit root) and the alternative hypothesis being stationarity (Pesaran et al. 1999). The results suggest that the majority of the variables are integrated of order 1 (I(1)), meaning they are stationary after taking first differences. This highlights the importance of considering the stationarity of a time series when conducting empirical studies, as non-stationarity can affect the validity of results and interpretations.

Panel co-integration The results of the panel co-integration analysis presented in Table 9 are based on three different tests. According to the first test, the modified Phillips-Perron (PP) test proposed by Pedroni (2004), the *t* statistic of 2.8978 is significant at the 1% level, with a *p* value of 0.000 (Pedroni 2004). This suggests the presence of co-integration in the data. The results of the traditional Phillips-Perron test are also significant at the 1% level, with a *t* statistic of −8.2973 and a *p* value of 0.000 (Phillips and Perron 1988). These results provide evidence of co-integration in the data.

The second test, Kao's (1999) co-integration, involves applying various versions of the Dickey-Fuller test. All of these tests provide evidence of co-integration, as the *t* statistics are all significant at the 1% level (*p* value = 0.000). The final test, Westerlund's Edgerton's (2007) co-integration, is based on the variance ratio test. The *t* statistic for the variance ratio test is −1.289, which is significant at the 1% level (*p* value = 0.000). This again provides evidence of co-integration in the data. The results of the panel co-integration tests provide strong evidence of co-integration in the panel data.

Main results

Table 10 presents the results of a system generalized method of moments (GMM) analysis of the relationship between various economic variables and five sectors in the country: the nationwide sector, the Eastern sector, the Northeast sector, the Central sector, and the Western sector. The study investigated how independent variables (trade openness, industry structure, foreign direct investment, renewable energy consumption, technological innovation, human capital, government effectiveness, and government budget) influenced green finance development efficiency in China. The study further investigated whether controlling variables such as tertiary industry, economic policy uncertainty, economic development, and urbanization rate influence green finance development efficiency in China.

Overall, the study found that trade openness, industry structure, foreign direct investment, technological innovation, human capital, and government budget positively and significantly influenced green finance development efficiency in China with respective coefficient values of 0.1284, 0.4128, 0.2382, 0.3183, 0.0142, and 0.2708. This implies that a unit increase in these variables could significantly increase Chinese green finance development efficiency. However, renewable energy consumption negatively influenced green finance development efficiency such that a reduction in renewable energy consumption could significantly reduce green finance development efficiency by −0.8109.

The *t* statistics indicate the strength of the relationship between the independent and dependent variables. A higher *t* statistic indicates a stronger relationship. The results also show the goodness of fit of the model through the adjusted R^2, which ranges from 0.7807 to 0.8592, with a probability of *F* statistic less than 0.0001. This suggests that the model explains a significant portion of the variability in the dependent variable. The AR(1) and AR(2) are tested to examine the autocorrelation of the residuals, and the results indicate that there is no significant autocorrelation in the residuals. The Hansen test and Sargan test results suggest that the overidentification restrictions are satisfied in the nationwide sector. The Hansen and Sargan tests show the validity of the model. Wald's chi^2 test shows the significance of the independent variables in the model, with a probability of less than 0.0001. Finally, the *J* statistic suggests the

Table 10 Empirical result from system GMM

	Nationwide		Eastern sector		Northeast sector		Central sector		Western sector	
GFDE	β	*t* stat	β	*t* stat	β	*t* stat	β	*t* stat	β	*t* stat
lnTOS	0.1284**	1.91	0.2119**	1.38	0.2721*	4.11	0.0231**	3.19	0.0203**	2.23
lnIS	0.4128*	8.42	0.2290*	3.13	0.8992**	2.39	0.2481*	9.29	1.0922**	1.89
lnFDI	0.2382*	5.12	0.0219**	4.29	0.4534*	4.62	0.4782**	7.20	0.8928	4.22
lnREC	−0.8109**	−6.29	−0.8290*	−3.79	−0.3526**	−4.83	−0.2869**	−3.29	−0.0341**	−1.79
lnTI	0.3183**	−3.19	0.2061**	4.20	0.3598**	4.14	0.0284**	6.28	0.0673**	3.29
lnHC	0.0142*	1.09	0.2512	0.96	0.0123*	2.12	0.0178	2.81	0.0862**	2.10
lnGE	0.2891	3.56	0.0189**	4.38	0.2759	4.04	0.0783**	3.86	0.0834	2.84
lnGB	0.2708*	8.92	0.0792	6.92	0.0671*	3.83	0.3891**	5.49	0.9378	3.60
lnGDP	0.4892**	5.82	0.0287**	8.02	0.3810**	1.84	0.2839*	2.73	0.0383*	5.29
lnUR	−0.8328**	−4.29	−0.0379**	−3.69	−0.0482**	−1.79	−0.0783**	−5.20	−0.7820**	−4.29
lnEPU	−0.7201*	−3.84	−0.0382*	−8.93	−0.0692**	−2.48	−0.2680**	−7.39	−0.0279**	−3.73
lnTIR	−0.3802**	−4.89	−0.0281	−3.41	−0.0392	−8.04	−0.7692	−6.39	−0.0486**	−2.83
Con	0.3392**	2.94	0.2209**	2.42	0.1622*	4.19	0.0792*	4.72	0.0693**	5.78
AR(1)	4399 (0.002)		3105 (0.001)		2053 (0.001)		3418 (0.013)		4823 (0.020)	
AR(2)	3092 (0.413)		2724 (0.369)		4202 (0.204)		3157 (0.153)		2732 (0.823)	
Hansen test	45.28 (0.289)		32.62 (0.384)		39.43 (0.252)		50.33 (0.196)		48.22 (0.102)	
Sargan test	389.24 (0.279)		313.42 (0.168)		342.49 (0.241)		402.61 (0.307)		309.43 (0.418)	
Wald's chi^2/R^2	5205.92 (0.001)		4983.81 (0.000)		5125.08 (0.000)		4932.69 (0.001)		4839.10 (0.000)	
r^2	0.8052		0.8592		0.8113		0.8092		0.8067	
Adjusted r^2	0.8012		0.8509		0.8039		0.8178		0.7807	
Prob > *F*	641.81 (0.000)		596.83 (0.000)		489.84 (0.000)		605.67(0.001)		479.28(0.0001)	
J statistic	478.30		459.26		448.93		380.72		319.43	

*, **, and *** signify 1%, 5%, and 10% significance levels, respectively

overidentifying restrictions of the model, with values ranging from 319.43 to 478.30. A lower *J* statistic indicates a better fit of the model.

For example, in the Eastern sector, a negative relationship was found between TOS and GFDE, with a *t* statistic of −1.38 and a significance level of 0.05. In the Northeast sector, a positive relationship was found between FDI and the sector, with a *t* statistic of 4.62 and a significance level of 0.05. Similarly, in the Western sector, a positive relationship was found between GC and the sector, with a *t* statistic of 2.84 and a significance level of 0.05. The study provides insights into the factors that drive green transformation and the role that green finance plays in supporting sustainable development. By understanding the relationship between GFDE and other variables, the study seeks to inform policies and strategies that can promote green transformation and support the transition toward a more sustainable economy.

Robustness checks

The study further performed post-estimation diagnoses after developing the dynamic GMM framework. The study tested for serial correlation, and the overall validity of the instrumental variables as seen in Table 10. In order to ensure the robustness and accuracy of the findings of the study, the fixed-effect model was further engaged in estimating the behavior of influencing factors in the regional GFDE of China.

The results of the robustness check suggest that the coefficients for the independent variables are statistically significant for all the sectors, except lnIS in the Northeast sector. The magnitude of the coefficients varies between the different sectors, with the Eastern and Northeast sectors having the smallest magnitude. The *t* statistics indicate that the coefficients are significant at the 1%, 5%, and 10% levels for most of the variables.

In terms of model fit, the results indicate that the models have a good fit, as indicated by the adjusted *R*-squared values, which range from 0.6822 to 0.7319, and the *p* values of the *F* statistics, which are all below 0.05, indicating that the models are statistically significant. The Akaike information criterion and Schwartz criterion values suggest that the models have a good fit, with values ranging from 1.2839 to 1.8322. The chi^2 values indicate that the models fit the data well, with values ranging from 5.8482 to 7.5693. The Hausman test results suggest that the fixed-effect models are preferred over the random-effect models, with *p* values ranging from 0.002 to 0.0762 (Table 11).

Both analyses conducted suggest that the independent variables have a significant impact on the dependent variable. The results in both regression analyses support the hypothesis that the independent variables (lnTOS, lnIS, lnFDI, lnREC, lnTI, lnHC, lnGC, lnGB, lnGDP, lnUR, lnEPU, lnTIR) have a positive or negative effect on the dependent variable (GFDE). However, the robustness check using the fixed-effect estimation provides additional assurance that the results obtained from the GMM system are not just due to random fluctuations but are robust and reliable.

Discussions

Improvement of regional green financial development efficiency measure in China towards sustainable development

The present study aimed to examine the green financial development efficiency in 30 provinces of China using the dynamic SBM-DEA model. This model was chosen for its ability to incorporate the dynamic nature of the regions and its ability to include undesirable output, such as industrial waste, in its efficiency calculations. The results of the study showed that China has a good green financial development efficiency of 0.7867, implying that the country is contributing to sustainable development through green financial activities.

The study found that provinces with heavy industrial and economic activities, such as Jiangsu and Tianjin, have a higher green financial development efficiency. However, there is an imbalance in the development level of green finance between the Eastern, Northeast, Central, and Western regions of China. The Eastern region had the highest GFDE of 0.8732, while the Northeast and Western sectors had losses of over 28% in sustainable development through their financial activities. The results also showed an upward trend in green finance development in China, but there were still significant challenges, including imperfect infrastructure, inadequate laws and regulations, and a lack of understanding among financial institutions and businesses. The study highlights the need for improvement in the green financial development efficiency in the Northeast and Western regions, which recorded a low GFDE.

Overall, the study provides a comprehensive examination of the regional green financial development efficiency in China and sheds light on the disparities in green finance development between regions. Further research could be conducted to evaluate the impact of various policies and initiatives aimed at improving the level of green finance development in China. This supports the findings of Hu et al. (2020), Tang et al. (2022), and Lu et al. (2022) that China's green financial development efficiency has improved in recent years.

The findings of the study on green financial development efficiency (GFDE) in China provide important insights into the state of green finance in the country and its role in promoting sustainable development. The study highlights the importance of various factors, including tertiary openness,

Table 11 Robustness check using fixed effect

	Nationwide		Eastern sector		Northeast sector		Central sector		Western sector	
GFDE	β	*t* stat	β	*t* stat	β	*t* stat	β	*t* stat	β	*t* stat
lnTOS	0.0332*	3.46	0.0364**	3.28	0.1048*	3.73	0.1419**	4.96	0.1978*	5.72
lnIS	0.32487**	2.19	0.0199**	4.20	0.2422*	1.85	0.3591*	5.04	0.9379**	4.03
lnFDI	0.1890*	3.22	0.2939*	3.53	0.2178*	3.83	0.3778*	4.73	0.7989**	2.10
lnREC	−0.0839**	−4.03	−0.0690*	−2.04	−0.2392*	−3.38	−0.2394**	−5.19	−0.3881**	−3.52
lnTI	0.4832*	3.82	0.0361	3.73	0.8682	2.49	0.1904*	2.82	0.0923	5.09
lnHC	0.393*	4.25	0.1893*	1.94	0.2493	5.74	0.4978	3.52	0.5627**	4.39
lnGE	0.4893	4.28	0.1327	5.23	0.1890	1.83	0.1426**	4.63	0.0349	3.96
lnGB	0.4728**	5.5	0.0793**	6.58	0.4753	4.31	0.0141	6.25	0.0128**	2.48
lnGDP	0.3289*	4.69	0.2227	3.62	0.1383	2.19	0.0232**	3.49	0.6093	4.36
lnUR	−0.3014**	−3.39	−0.1235*	−9.13	−0.2184	−2.48	−0.5024*	−1.42	−0.0530**	−3.34
lnEPU	−0.0382**	−4.92	−0.1391	−6.13	−0.4182	−3.29	−0.281**	−3.48	−0.0439	4.98
lnTIR	0.2118**	3.24	0.0381**	2.72	0.142	4.10	0.2012*	4.02	0.4820**	4.52
Con	0.1015*	3.41	0.0112*	3.14	0.2138	3.21	0.0241*	3.24	0.311**	3.18
SE of regression	0.6738		0.5782		0.5382		0.5728		0.5892	
Akaike info criterion	1.6793		1.7839		1.4892		1.2839		1.8322	
Scharwz criterion	2.2780		2.7803		2.4378		2.8730		2.7432	
Chi^2	6.3489		7.5693		6.0679		7.3679		5.8482	
r^2	0.7037		0.6936		0.7083		0.6928		0.7149	
Adjusted r^2	0.6822		0.7102		0.7215		0.7029		0.7319	
Prob > *F*	41.20 (0.000)		23.73 (0.000)		42.83 (0.000)		37.13(0.000)		28.78(0.000)	
Hausman test	0.0762		0.0278		0.0387		0.0402		0.002	

*, **, and *** signify 1%, 5%, and 10% significance levels, respectively

industry structure, foreign direct investment, renewable energy consumption, technological innovation, human capital, government effectiveness, and government budget, in improving GFDE (Zhou and Tian 2019).

However, the study also highlights the challenges in measuring GFDE and the need for further refinement of the measure. For example, the study suggests that the current GFDE measure may not fully capture the complex and dynamic nature of green finance and the challenges posed by the transition to renewable energy. As such, there is a need to improve the measure to better reflect the state of green finance in China and its role in promoting sustainable development. One possible way to improve the GFDE measure is to include more comprehensive and up-to-date data sources, such as data from private sources and international organizations. This will provide a more accurate and comprehensive picture of the state of green finance in China and its role in promoting sustainable development. Additionally, the measure can be refined to better capture the unique challenges posed by the transition to renewable energy and the role of green finance in supporting this transition (Fang et al. 2019; Liu and Liu 2020).

Another way to improve the GFDE measure is to incorporate more nuanced and sophisticated analytical tools, such as machine learning algorithms, to better capture the complex and dynamic nature of green finance and its role in promoting sustainable development. These analytical tools can help to identify the key drivers of GFDE and provide valuable insights into the challenges and opportunities posed by the transition to renewable energy.

The findings of the study on GFDE in China provide important insights into the state of green finance in the country and its role in promoting sustainable development. However, there is a need to improve the measure to better reflect the complexities and challenges of green finance and its role in supporting the transition to renewable energy. Policymakers can use the findings of this study to prioritize the key drivers of GFDE and support the green transformation agenda in pursuit of sustainable development.

Influencing factors of green financial development in China in achieving sustainable development

The present study aims to examine the impact of various factors on the efficiency of green financial development (GFDE) in China, with a view to promoting sustainable development. The independent variables, such as tertiary openness (TOS), industry structure (IS), foreign direct investment (FDI), renewable energy consumption (REC), technological innovation (TI), human capital (HC), government effectiveness (GE), and government budget (GB), are anticipated to positively influence GFDE. Meanwhile, the controlling variables, such as economic development (GDP), urbanization rate (UR), economic policy uncertainty (EPU), and tertiary industry proportion (TIR), may have either a positive or negative impact on GFDE. The findings of this study provided a deeper understanding of the drivers of green transformation and the role of green finance in supporting sustainable development. By exploring the relationship between GFDE and other variables, the study will inform policy-making and strategy development to promote green transformation and support the transition towards a more sustainable economy.

Sustainable development balances economic, social, and environmental considerations to meet the needs of the present generation while preserving the ability of future generations to meet their own needs. Green transformation, in this context, refers to the shift towards a low-carbon, environmentally friendly economy, hence improvement in GFDE. The study measures GFDE as a performance indicator of the green finance sector, incorporating both the input and output dimensions of green finance. The independent variables in the study provided important insights into the factors that influence green transformation and sustainable development. The findings related to the independent variables can help policymakers identify the key drivers of green finance efficiency (GFDE) and prioritize these factors in their policy decisions (Chen et al. 2022b; Lv et al. 2021a, b). For example, the study found that trade openness (TOS) has a positive impact on GFDE, suggesting that increasing trade openness in trade and investment can positively impact the efficiency of green finance. This finding highlights the importance of promoting international trade and investment in supporting green transformation and sustainable development. Policymakers can use this information to facilitate cross-border trade and investment in green finance and promote a more globally integrated green finance market.

Moreover, a significant and positive impact of industry structure (IS) on GFDE suggests that a well-structured industrial sector can positively impact the efficiency of green finance. This finding highlights the importance of promoting a diverse and well-functioning industrial sector in supporting green transformation and sustainable development. Policymakers can use this information to promote a well-structured industrial sector that supports the growth of green finance and provides a foundation for sustainable development.

The study further found that foreign direct investment (FDI) has a positive impact on GFDE, revealing that increasing foreign investment can positively impact the efficiency of green finance. This finding highlights the importance of promoting foreign investment in green finance and sustainable development. Policymakers can use this information to attract foreign investment in green finance and promote cross-border cooperation in sustainable development.

In the same vein, it was found that renewable energy consumption (REC) has a negative impact on GFDE. This implies that increasing reliance on renewable energy can negatively impact the efficiency of green finance. This finding highlights the challenges posed by the transition to renewable energy for green finance and sustainable development. Policymakers can use this information to address the challenges of the transition to renewable energy and promote a more sustainable energy mix. The findings are in tandem with the findings of Liu et al. (2019), Sun et al. (2022), and Xu et al. (2022a) that FDI, renewable energy consumption, and industry structure have a significant impact on GFDE in China.

The findings related to the independent variables can provide valuable insights into the key drivers of green transformation and sustainable development. Policymakers can use this information to prioritize these drivers and support the green transformation agenda in pursuit of sustainable development.

The controlling variables in the study can also have important implications for green transformation and sustainable development. The findings related to the controlling variables can help to understand the role they play in shaping the relationship between the independent and dependent variables. For example, the positive effect of economic development (GDP) on green financial development efficiency (GFDE) indicates that should economic development increase, efficiency of green finance also increases. The findings of this study contradict the findings of Zhou et al. (2022). This is an important finding as it highlights the importance of economic growth in promoting green finance and sustainable development. Policymakers can use this information to prioritize economic development in their policy decisions to support green transformation.

Similarly, researchers found that the urbanization rate (UR) has a negative impact on GFDE. This suggests that an increase in the urbanization rate would decrease the efficiency of green finance in China. In the same vein, economic policy uncertainty (EPU) has a negative impact on GFDE. This is important because it highlights the need for stability and predictability in economic policy to promote green finance and sustainable development. Policymakers can use this information to reduce economic policy uncertainty and create a more stable policy environment for green finance. The findings related to the controlling variables can provide a deeper understanding of the interplay between different factors and their impact on green transformation and sustainable development.

Conclusions, recommendations, and limitations

Conclusions

The conclusion was based upon the findings of the study examining the role of green financial development efficiency in the pursuit of a green transformation agenda in China towards achieving sustainable development. The findings show that green financial development efficiency plays a significant role in promoting the green transformation agenda in China, as it provides the necessary resources and incentives for firms to adopt environmentally friendly practices and technologies. This will help China to achieve green transformation and also help in achieving sustainable development across all the 30 provinces involved in the study. The results of this study, along with previous research, highlight the importance of green finance in driving the country's transition toward a more sustainable future.

This conclusion aligns with the findings of previous studies in the field. For example, a study by Li et al. (2021) found that green finance can play a crucial role promoting sustainable development in China. The findings of the argument are the essence of green finance development efficiency in providing financial incentives and resources to firms, encouraging them to invest in green technologies and projects. Additionally, it can be inferred that green finance development in China can help to mitigate the risks associated with the transition to a green economy, providing a stable source of funding for the development of green technologies and projects. The finding can help to mitigate the financial risks associated with green investments, providing a stable source of funding for environmentally friendly projects. To sum up, the study highlights the importance of green financial development and its potential to support China's transformation to a green and sustainable economy.

Recommendations

Based on the findings of this study, it is recommended that the government should continue to prioritize the development of a green financial sector to advance sustainability. This can be achieved by establishing a supportive environment for green finance, providing financial support for environmentally friendly projects, and improving related regulations and policies. In addition, the government should focus on fostering the growth of green industries and capital as these are critical to sustainable development. To further enhance the effectiveness of green financial development in China's pursuit of sustainability, the following steps should also be considered as illustrated in Fig. 7.

As seen in Fig. 7, the government and regulatory bodies can create an attractive environment for green investment by offering tax incentives, subsidies, and other financial benefits. This will not only draw more investment but also drive the growth of green technologies and businesses. The financial sector should support green investment by offering a range of green financial products, such as green bonds, funds, and loans, to make it easier for individuals and businesses to participate in environmentally friendly projects and technologies. The government can raise awareness about the significance of green finance and its role in sustainability through financial education and training programs for the public, banks, and other financial institutions. Moreover, in order to ensure effective monitoring and enforcement of green investment and development policies, the role of environmental protection agencies in China should be strengthened. Again, a closer collaboration between the financial sector and environmental protection agencies is essential to achieve sustainable development. This can be accomplished by creating a regulatory framework that facilitates cooperation and information sharing between the two sectors. To align with global best practices, China should adopt international environmental standards such as ISO 14001 and integrate them into its green finance policies. This will also attract more foreign investment. Lastly, to assess the effectiveness of green finance policies and make necessary adjustments, regular reviews and evaluations of their impact on sustainable development should be conducted. This will help ensure that green finance policies remain relevant and up-to-date in promoting sustainability.

Limitation and future studies

This study is subject to certain limitations. Firstly, the data used in this study only covers the period from 2010 to 2020, and the current situation may have changed. Secondly, the study only considers a limited number of variables, and there may be other important factors that are not included in the analysis. The study relies on publicly available data and may not capture the entire picture due to limitations in data quality, completeness, and accuracy. The study focuses on a limited time horizon, which may not fully capture the long-term impact of green financial development on sustainable development. Furthermore, the study focuses on correlations between green financial development efficiency and sustainable development, but causality cannot be established due to the limitations of the data and methodology used. The study only focuses on the situation in China and may not be generalizable to other countries.

The findings of this study provide valuable insights into the role of green financial development efficiency in achieving sustainable development in China. The results indicate

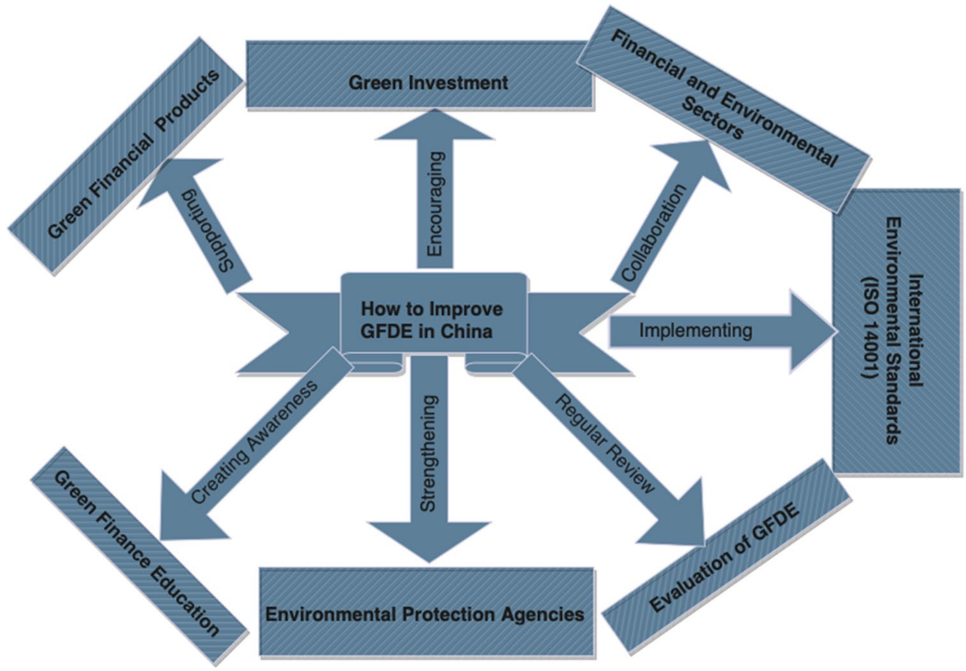


Fig. 7 Recommendation framework

that the development of green finance is crucial in promoting the green transformation agenda and achieving sustainable development. However, further research is needed to explore other factors that may influence the relationship between green financial development efficiency and sustainable development, and to examine the effectiveness of the policies and regulations related to the green financial sector. The concept of green financial development is still evolving and may be subject to changes and refinements over time. Further research is needed to understand how these challenges can be overcome and how the efficiency of green financial development can be improved. Other research scholars could explore the long-term effects of green finance on sustainable development in China, as well as the potential challenges and obstacles that may arise in the implementation of green finance programs. Moreover, it is suggested that future researchers explore the mechanisms that exist for financing green initiatives and projects, as well as their effectiveness in driving sustainable development in China. This could include examining green bonds, sustainable investment funds, and other forms of green finance.

It is important to note that while these limitations exist, they do not detract from the overall significance of the study. By acknowledging and understanding the limitations, future research can build on the findings and address the limitations in future studies.

Author contribution FAS: conceptualization, literature review, and final manuscript. PS: literature review and final manuscript. GN: analysis and discussion. OEA: investigation and conceptualization. AI: formal analysis and proof reading. BBC: data collection and visualization. KFK: proof reading and literature review.

Data availability The datasets used publicly accessible data.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

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Conflict of interest The authors declare no competing interests.

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