Archives of Environmental Protection
Vol. 52 no. 1 pp. 118–135

PL ISSN 2083-4772
DOI: 10.24425/aep.2026.158388

© 2026. The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution-ShareAlike 4.0 International Public License (CC BY SA 4.0, https:// creativecommons.org/licenses/by-sa/4.0/legalcode), which permits use, distribution, and reproduction in any medium, provided that the article is properly cited.

Green Finance Instruments and Carbon Dioxide Emission Intensities: A Generalized Additive Mixed Models Analysis

Wong Ming Wong[1], Xing Wang[2], Tiantian Liu[3], Wunhong Su[4]*

[1] Krirk University, Thailand
[2] Shandong Agriculture and Engineering University, China
[3] Assumption University, Thailand
[4] Hangzhou Dianzi University, China

*Corresponding autor`s e-mail: whsu@hdu.edu.cn

Keywords: green finance; carbon dioxide emission intensity; generalized additive mixed models; gross domestic product; time series

Abstract: This study aims to examine the impact of green finance instruments on carbon dioxide emission intensity (CDEI), filling a methodological research gap across regions and time-series data. Specifically, it investigates how green finance instruments, namely green credit, green support, and green funds, together with gross domestic product (GDP), affect the CDEI across diverse regions from 2008 to 2021. A generalized additive mixed model (GAMM) was used to analyze panel data from 29 municipalities and provinces in China over this period. These municipalities and provinces were grouped into six administrative regions, allowing the model to capture the nonlinear relationships and interactions that vary across space and time. The results indicate that in Northern, Northeastern, and Northwestern China, GDP is associated with a higher CDEI. In contrast, green credit, green support, and green funds did not significantly reduce the CDEI during the study period. This study contributes to the discussion on the importance of developing region-specific green finance strategies. It proposes policy approaches tailored to local economic conditions to improve the effectiveness of green finance efforts, thereby supporting emission reduction and advancing environmental policies and sustainable business strategies.

Introduction

Green finance refers to financial products, services, and policies that aim to support environmentally sustainable activities while promoting social responsibility (Ante, 2024; van Niekerk, 2024; Zairis et al., 2024). Green finance instruments include various financial products such as green bonds, loans, insurance, and investments in renewable energy and eco-friendly infrastructure (Fan et al., 2024; J. Wang et al., 2024; Yu et al., 2023; Zhou et al., 2024). This approach integrates financial systems with ecological sustainability goals, ensuring that economic development does not occur at the expense of environmental integrity. Green finance contributes to global climate change mitigation by funding projects that reduce carbon emissions, conserve natural resources, and foster sustainability.

The relationship between green finance and other variables, such as economic growth and carbon emissions, has also been discussed (Ante, 2024; van Niekerk, 2024). Green finance promotes low-carbon energy development by investing in renewable energy and environmentally friendly technologies, while simultaneously fostering economic growth through job creation and industrial development in low-emission sectors. Furthermore, green finance is guided by environmental, social, and governance (ESG) criteria to ensure that financial investments contribute to environmental sustainability and social well-being (Zairis et al., 2024). As green finance becomes increasingly integrated into global financial systems, its role in promoting sustainability and inclusive economic growth has become more evident (Ante, 2024; Zhou et al., 2024).

Previous studies on green finance have adopted datasets from sources such as the OECD, Bloomberg, the World Bank, and China Stock Market and Accounting Research (CSMAR) database (Banerjee et al., 2024; Huang, 2024; Susan & Pan, 2024; Tufail et al., 2024; J. Wang et al., 2024). Specifically, studies on green finance in China mainly rely on two types of data sources (Cui et al., 2024; Fan et al., 2024; Lian et al., 2024; Liang & Yang, 2024; Zhang et al., 2024). The first comprises firm-level data obtained from the Wind Economic Database (EDB) and the CSMAR database, which focus on publicly listed A-share companies (Cui et al., 2024; Liang & Yang, 2024; Safi et al., 2024). These datasets are frequently used to examine how green finance influences corporate behavior and sustainability performance, emphasizing its role in achieving environmental goals and mitigating climate change.

Second, some studies employ macro-level datasets, such as the *China Statistics Yearbook*, which provides detailed economic and environmental indicators at the county and provincial levels (Fan et al., 2024; Liu et al., 2024; Zhang et al., 2024). These data include gross domestic product (GDP), unemployment rates, and green investment ratios (Wei, 2024). Additionally, regional statistical yearbooks and environmental reports offer insights into the spatial effects of green finance across different regions (Lian et al., 2024; Liu et al., 2024). Collectively, these datasets allow researchers to explore the impact of green finance on economic resilience, market integration, and corporate behavior in China.

However, most existing studies on green finance use econometric methods, such as panel-data regression models, to examine the effects of green finance on corporate behavior and regional economic resilience (Wei, 2024). Fixed-effects models are commonly used to control for unobservable variables, thereby improving the accuracy of estimated impacts (Zhang et al., 2024; Zhao, 2024). Some studies incorporate interaction terms to investigate how factors such as climate risk, financial constraints, and market integration shape the relationship between green finance and corporate innovation (Li & Xu, 2024; Liang & Yang, 2024). Additionally, reliability checks, such as lagged regression models, are often conducted to verify the consistency of the findings (Wei, 2024). These methodologies provide comprehensive insights into the impact of green finance on sustainability outcomes across different regions in China.

Nevertheless, important research gaps remain in studies that rely primarily on panel-data regression, regression models, and fixed-effects models to analyze categorical and time-series variables (Fan et al., 2024; Zhang et al., 2024; Zhou et al., 2024). For example, Zhang et al. (2024) employed the Generalized Method of Moments (GMM) to analyze the green finance and CDEI data from 30 municipalities and provinces from 2006 to 2020, assuming linear relationships and normally distributed error terms. Similarly, Fan et al. (2024) used a regression model to examine the relationships among green finance, carbon emissions, and air pollution using data from 2008 to 2015.

These studies assume linear relationships between explanatory and response variables (Fan et al., 2024; Li & Xu, 2024; Wang et al., 2023; Xie et al., 2024; Zeng et al., 2024; Zhao, 2024), which may fail to capture nonlinear dynamics and hierarchical data structures. In this study, unobserved regional heterogeneity refers to unmeasured differences across provinces in industrial structure, energy use, and policy enforcement. Conventional linear and spatial panel models treat such heterogeneity as time-invariant fixed effects, rely on spatial weight matrices, and impose linear associations among green finance, GDP, and the CDEI. In contrast, a Generalized Additive Mixed Model (GAMM) relaxes these constraints by incorporating smooth functions to model nonlinear effects, fixed and random effects to capture regional heterogeneity, and flexible link functions that allow for non-normal response distributions. As a result, GAMM is particularly suitable for the structure of the present dataset.

GAMM provides significant benefits for analyzing complex datasets, particularly in ecology, economics, and the social sciences (Augustin et al., 2013; Feng, 2022; Wong et al., 2024b). It effectively captures nonlinear relationships between predictors and response variables, making it suitable when linear assumptions are violated. Moreover, GAMM accommodates both fixed and random effects, allowing for the analysis of grouped or hierarchical data, and provides flexibility in selecting smoothing parameters to prevent overfitting. Additionally, it can handle non-normal distributions and model nonlinear trends, time-series dynamics, and panel-data correlations through smoothing techniques.

Accordingly, this study aims to examine the relationships among green finance instruments, GDP, and CDEI using GAMM. Green finance refers to green financial instruments, such as green bonds, loans, and insurance that support environmentally sustainable projects, including renewable energy, energy efficiency, and pollution control initiatives (Wei, 2024; Yu et al., 2023; Zhang et al., 2024). Carbon emissions originate from the release of carbon dioxide and other greenhouse gases, primarily from fossil fuel combustion, industrial processes, and deforestation (Lian et al., 2024). Furthermore, the CDEI metric is often used to evaluate the environmental impact of economic activities by quantifying carbon dioxide emissions per unit of economic output, calculated as the ratio of total carbon dioxide emissions to GDP (Guo et al., 2024; Sharma, 2011).

Literature review

This section covers four topics: (a) an overview of green finance, (b) CDEI, (c) carbon emissions, (c) green finance and CDEI, (d) GAMM, and (e) recent empirical applications of GAMM.

Green finance

This study defines green finance as encompassing a range of financial instruments, such as green credit, green investment, green insurance, green bonds, green support, green funds, and green equity. Green finance refers to financial services and products designed to support environmental sustainability while incorporating social responsibility into financial activities (Fan et al., 2024; Liang & Yang, 2024; J. Wang et al., 2024; Wei, 2024; Zhou et al., 2024). It focuses on channeling financial resources toward environmentally friendly and sustainable projects, such as renewable energy, green infrastructure, and eco-friendly industries (Cui et al., 2024; J. Wang et al., 2024). Such financial mechanisms are essential for promoting environmental protection, reducing carbon emissions, and driving sustainable economic growth (Liang & Yang, 2024; Wei, 2024). By providing instruments such as green credit, bonds, and investments, green finance encourages companies to prioritize sustainability in their operational and investment decisions, thereby fostering regional economic resilience and environmental sustainability (J. Wang et al., 2024; Yu et al., 2023).

Carbon dioxide emission intensity

This study adopts the Carbon Dioxide Emission Intensity (CDEI) metric, which measures carbon dioxide emissions per unit of economic output and is commonly expressed as emissions per unit of GDP (Guo et al., 2024). It is calculated as:

$$CDEI = \frac{CO_2 Emissions}{GDP}$$

This indicator assesses the efficiency with which an economy generates output while minimizing carbon emissions (Guo et al., 2024). Lower CDEI values indicate a more efficient, less carbon-intensive economy, whereas higher values reflect greater carbon intensity. Several factors influence CDEI, including technological innovation, energy mix, and economic structure (Sharma, 2011). Economies heavily reliant on fossil fuels, such as coal, tend to exhibit higher CDEI levels, whereas those that incorporate renewable energy sources tend to exhibit lower CDEI levels (Lv et al., 2024).

Understanding the relationship between carbon emissions and CDEI is essential for advancing environmental sustainability. While total carbon emissions represent absolute CO_2 output, CDEI reflects emissions relative to economic activity. When economic growth outpaces carbon emissions, CDEI declines, indicating improved efficiency. Conversely, when emissions rise faster than economic growth, CDEI increases, indicating inefficiency (Guo et al., 2024). Technological advancements play a pivotal role in reducing both emissions and CDEI, as evidenced by industrialized economies adopting energy-efficient technologies and transitioning toward greener industries (Guo et al., 2024; Lv et al., 2024).

Green finance and carbon dioxide emission intensity

Green finance plays a critical role in promoting sustainable economic growth while mitigating environmental challenges (Cui et al., 2024; Wei, 2024). Several studies indicate that green financial instruments, particularly green bonds and green credit, reduce CDEI (Fan et al., 2024; Lian et al., 2024; Liang & Yang, 2024; Zhou et al., 2024) and foster green growth (Tufail et al., 2024). As investment in green finance increases, its impact on green growth also increases (Tufail et al., 2024). For example, green bonds finance renewable energy projects, thereby decreasing reliance on fossil fuels and lowering carbon emissions (Lian et al., 2024; C. Wang et al., 2024). Their effectiveness is further enhanced when funds are allocated to new projects rather than refinancing existing ones, particularly when external reviews verify compliance with environmental standards (Safi et al., 2024; Wei, 2024).

Additionally, green finance facilities corporate disclosure of environmental, social, and governance (ESG) information by easing financing constraints, primarily through green credit mechanisms (Liang & Yang, 2024). Other instruments, such as green bonds, also promote ESG transparency, although their effects differ. These findings highlight the importance of green finance in advancing energy development and corporate accountability, despite regional disparities in its distribution (Liang & Yang, 2024). More specifically, green finance reduces carbon emissions by funding environmentally sustainable initiatives, such as renewable energy and pollution control technologies (Zhou et al., 2024). Different green finance instruments exert heterogeneous impacts on CDEI (Fan et al., 2024; Liu et al., 2024; Zhou et al., 2024). Green bonds support large-scale renewable energy projects, while green credit offers favorable loans for cleaner production technologies. Green investment funds enable firms to develop carbon-reducing innovations, and carbon trading mechanisms incentivize emission reductions by allowing firms to trade carbon credits (Zhou et al., 2024).

Empirical evidence from China demonstrates that green finance instruments, such as green credit and bonds, reduce CO_2 and SO_2 emissions (Fan et al., 2024; Liu et al., 2024; Zhou et al., 2024), whereas green insurance, green support, and green equity show weaker or insignificant effects (Fan et al., 2024). In contrast, Zhang et al. (2024) found that four green finance instruments, namely green credit, green investment, green insurance, and green support, effectively reduce CDEI through generalized method of moments GMM estimation. These instruments restrict financing to high-energy industries, redirect funds toward environmental pollution control, promote sustainable agricultural practices, and strengthen green policies through environmental funding (Zhang et al., 2024).

Several studies have examined the regional and sectoral impacts of green finance on energy development and ESG disclosure in China (Lian et al., 2024; Liang & Yang, 2024). Using data from 30 provinces from 2011 to 2021, Lian et al. (2024) found that green finance promotes energy development, with major cities such as Beijing and Shanghai acting as regional hubs that stimulate progress in neighboring areas. However, northern and western regions benefit less from these effects, reflecting persistent spatial disparities in the allocation of green financial resources.

Specifically, some studies have identified key factors influencing carbon emissions in China's municipalities and sectors (Liu et al., 2022; C. Wang et al., 2024; J. Wang et al., 2024; Xie et al., 2024). For example, Liu et al. (2022) examined carbon emissions in Beijing, Tianjin, Shanghai, and Chongqing, concluding that GDP and population growth are the main drivers of increased emissions, whereas improvements in industrial structure and energy composition contribute to reductions in emissions. The energy sector benefits significantly from investments in clean energy, leading to marked reductions in dependence on fossil fuels. In contrast, sectors such as mining face higher adaptation costs, which slow their transition toward sustainable practices and result in comparatively weaker emission reductions (C. Wang et al., 2024).

Case studies further illustrate these dynamics (Liu et al., 2024; Xie et al., 2024). Beijing has achieved significant emission reductions through industrial restructuring and progressive energy policies, underscoring the crucial role of megacities in China's decarbonization strategy. In contrast, Chongqing has experienced substantial emission growth, highlighting the need for sector-specific policies and targeted interventions. Moreover, foreign direct investment, energy structure, property rights, capital intensity, and research and development expenditures significantly affect China's industrial emissions from 2009 to 2021, indicating that technological innovation and institutional reforms are critical for sustainable industrial transformation (Xie et al., 2024).

In summary, green finance plays a pivotal role in reducing CDEI and advancing green economic growth (Wei, 2024). Green financial instruments, such as green bonds, green credit, and ESG investments, contribute to emission reductions by funding environmentally sustainable projects and promoting ESG disclosure (Fan et al., 2024; Liang & Yang, 2024; Zhou et al., 2024). However, the magnitude of these effects varies across sectors and regions. While the energy sector benefits substantially, industries such as mining face greater adjustment costs, leading to slower emission reductions (C. Wang et al., 2024). Regional disparities persist, with major cities such as Beijing achieving notable progress, whereas northern and western regions lag (Lian et al., 2024; Liu et al., 2024). These findings indicate the necessity of targeted financial interventions, technological innovation, and policy coordination to promote equitable and effective emission reductions across sectors and regions (Xie et al., 2024; Zhang et al., 2024).

Generalized additive mixed model

Previous studies on green finance frequently adopt the Spatial Durbin Model (SDM), which uses spatial lags and a spatial weight matrix to analyze spatial spillover effects (Bai et al., 2022; Fan et al., 2024; Li & Xu, 2024; Xie et al., 2024; Zeng et al., 2024; Zhao, 2024). However, SDM models the effects of explanatory variables, such as green finance and GDP, on outcomes, such as emissions, in a linear manner (Li & Xu, 2024). Similarly, GMM is used to address endogeneity in panel data but typically assumes linear relationships (Fan et al., 2025; Wang et al., 2023). Alternatively, panel models with structural breaks introduce nonlinearity by allowing relationships to change once a variable crosses the cutoff value (Bai et al., 2022; Mohy-ud-Din et al., 2025).

By comparison, GAMM uses smooth functions for covariates such as green finance, GDP, time, and region, enabling the modeling of continuous nonlinear effects (Brown-Schmidt et al., 2025). This methodology is specifically designed to capture complex nonlinear relationships while accounting for unobserved regional heterogeneity (Brown-Schmidt et al., 2025). Consequently, GAMM provides a distinct analytical perspective by prioritizing continuous nonlinear responses rather than modeling spatial spillovers or relying on discrete regime shifts defined by the cutoff values.

GAMM is based on the principles of Generalized Linear Models (GLMs) and Generalized Additive Models (GAMs). GLMs, developed by Nelder and Wedderburn (1972), extend linear models to accommodate non-normal distributions. Building on this framework, Hastie and Tibshirani (1986) developed GAMs, which allow for smooth nonlinear functions of predictor variables, thereby enhancing model flexibility. GAMM further extends GAMs by incorporating random effects, facilitating the analysis of complex data structures such as hierarchical or panel datasets. This integration of fixed and random effects with nonlinear relationships is particularly beneficial in ecology, economics, and the social sciences (Augustin et al., 2013; Feng, 2022; Wong et al., 2024b). As a result, GAMM has emerged as a powerful tool for modeling hierarchical or grouped time-series data. It offers enhanced flexibility in capturing fixed and random effects, accommodating time-series patterns, and modeling nonlinear relationships, thereby overcoming the limitations of traditional linear models (Ruppert et al., 2010; Wood, 2017; Zuur et al., 2009).

GAMM offers several advantages when dealing with complex datasets (Lin & Zhang, 1999; Pedersen et al., 2019; Wood, 2006, 2017). First, its ability to model nonlinear relationships between predictors and response variables is essential when linear assumptions are violated (Wood, 2006). Second, GAMM can accommodate both fixed and random effects, making it ideal for analyzing grouped or hierarchical data structures (Lin & Zhang, 1999). Third, GAMM provides flexible control over the smoothness of functions, enabling improved model fit without excessive overfitting (Wood, 2017). Finally, GAMMs can handle non-normal data distributions, increasing their applicability to real-world empirical problems (Pedersen et al., 2019).

Recent empirical applications of the generalized additive mixed model

Some empirical studies use GAMM when data exhibit spatial and temporal variation and display nonlinear patterns, as demonstrated by Augustin et al. (2013), Ferrari, Evangelista, Basiricò, et al. (2025), and Brown-Schmidt et al. (2025). These applications model smooth temporal and spatial trends while accounting for within-group correlation across observational units such as sites, regions, or individuals (Augustin et al., 2013; Ferrari, Evangelista, Basirico, et al., 2025; Wong & Su, 2025; Wong et al., 2024a, 2024b). The models incorporate random effects to capture group-level heterogeneity and variance components, thereby supporting inference for clustered and longitudinal data (Ferrari, Evangelista, Basirico, et al., 2025; Stram & Lee, 1994). Moreover, GAMM is well-suited to intensive time-series data with many observations per unit, such as eye-tracking or behavioral datasets, by integrating smooth functions with mixed-effects structures (Brown-Schmidt et al., 2025).

For example, in epidemiological and public health research, GAMMs relate incidence or risk outcomes to time-varying and spatial covariates while reducing residual autocorrelation (Cissoko et al., 2025; Feng, 2022; Wong & Su, 2025). Wong et al. (2024a) applied GAMM to model $PM_{2.5}$ concentrations in Singapore, Indonesia, and Thailand as smooth functions of time, incorporating random effects for spatial clusters and covariates representing COVID-19 control measures. Their findings showed that these measures were associated with lower $PM_{2.5}$ concentrations in Singapore and Indonesia, whereas no clear effect was observed in Thailand; nevertheless, the GAMM framework successfully captured distinct temporal dynamics across all three countries. Collectively, these studies highlight the necessity of modeling nonlinear covariate effects, within-unit dependence, and spatiotemporal structure within a unified framework, thereby justifying the adoption of GAMM.

Methodology

In this study, the GAMM is used to model regional heterogeneity in the CDEI. The six administrative regions in China differ in terms of industrial composition, energy mix, and policy implementation, and many of these factors are not fully observed. Linear or spatial panel models usually account for such differences by including fixed regional intercepts and linear covariate effects. In contrast, the GAMM incorporates smooth terms for GDP and time (SOL) and categorical effects for regions. This structure allows the relationship between GDP and CDEI to vary nonlinearly while controlling for systematic regional differences. As a result, part of the unobserved regional heterogeneity is captured through region-specific shifts and nonlinear response curves, rather than being constrained to a simple linear form. Because this study does not explicitly model spatial spillovers, the focus is on regional heterogeneity in levels and nonlinear trends rather than on spatial diffusion across neighboring provinces.

Data source

This study uses panel data from 29 municipalities and provinces in China covering the period from 2008 to 2021. The dataset comprises four groups of variables. First, green finance is measured using indicators of green credit, investment, bonds, insurance, support, funds, and equity (Xue & Kan, 2024; Zhang et al., 2024; Zhao, 2024). Second, carbon emission data were sourced from the Multi-resolution Emission Inventory for Climate and Air Pollution Research (MEIC) model, referred to as total carbon emissions (Zhang et al., 2024; Zhou et al., 2024). Third, GDP data were provided for the same 29 municipalities and provinces over the study period. Finally, the CDEI was calculated per capita using provincial-level data from 2008 to 2021 (Guo et al., 2024).

The dataset was obtained from multiple sources, including the China National Bureau of Statistics, Ministry of Science and Technology, and the People's Bank of China, as well as national and provincial statistical yearbooks, environmental bulletins, and specialized publications such as the *China Energy Statistical Yearbook*, *China Finance Yearbook*, *China Industrial Statistical Yearbook*, and *China Tertiary Industry Statistical Yearbook* (Xue & Kan, 2024; Zhang et al., 2024).

Instrument

This study considers four factors: green finance instruments, the CDEI, six regions, and a time index spanning 2008 to 2021. Table 1 presents the components of green finance, while Table AT1 in the appendix reports the measurement of the CDEI, regional classifications, and time variables.

The green finance instruments include green credit, investment, insurance, bonds, support, funds, and equity (Table 1). All variables are continuous in this study. The measurement of each financial instrument follows the definitions provided by Xue and Kan (2024) and Liu et al. (2023), while Nepal et al. (2024) and Zhao (2024) provide further illustrations, including detailed calculation formulas.

Each component of green finance is measured as a ratio using the formulas in Table 1. For example, green credit is defined as the share of loans allocated to environmental protection projects in total provincial credit; green support is the share of fiscal environmental protection expenditure in general budget expenditure; and green funds are the share of green fund market value in total fund market value. All green finance variables and GDP were standardized by subtracting the sample mean and dividing by the sample standard deviation, based on 406 observations (29 provinces × 14 years).

Second, carbon emissions are measured under Scope 1, Scope 2, and Scope 3 accounting standards, following the guidelines of the Intergovernmental Panel on Climate Change (IPCC) (Ding, 2024; Zhang et al., 2024; Zhao, 2024; Zhou et al., 2024).

(a) Scope 1 includes all direct greenhouse gas emissions occurring within the boundaries of each province, primarily

Table 1. . Green Finance Instrument

No	Instrument	Definition	Calculation Formula	Unit
1	Green Credit	Environmental Protection Project credit ratio	Green Credit = Total loans for environmental protection projects in the province / Total credit in the province	%
2	Green Investment	Investment in environmental pollution control accounts for a proportion of GDP	Green Investment = Environmental protection pollution control investment / GDP	%
3	Green Insurance	Promotion system of environmental pollution liability insurance	Green Insurance = Environmental pollution liability insurance investment / Total premium	%
4	Green Bonds	The extent of green bond development	Green Bonds = Total green bond issuance / Total amount of all bonds issued	%
5	Green Support	Proportion of financial environmental protection expenditure	Green Support = Financial environmental protection expenditure / General budget expenditure	%
6	Green Funds	Proportion of green funds	Green Fund = Total market capitalization of green funds / Total market capitalization of all funds	%
7	Green Equity	The scale of green stock equity of listed companies in each province.	Green Equity = Carbon trading, energy use rights trading, pollution rights trading / Total equity market transactions.	%

from transportation, building operations, industrial processes, land-use changes related to agriculture and forestry, and waste management practices.

(b) Scope 2 refers to indirect emissions from energy consumption that occur outside the province's jurisdiction but are associated with electricity, heating, and/or cooling purchased to meet the provincial demand.

(c) Scope 3 covers other indirect emissions arising from activities within the province but occurring outside its jurisdiction, excluding those included in Scope 2. These include emissions from the production, transportation, use, and waste treatment of goods purchased from outside the province.

Thus, total carbon emissions are calculated as: Carbon emissions = Scope 1 + Scope 2 + Scope 3.

Carbon emissions are measured in units of ten thousand tons of carbon dioxide.

The CDEI framework is described in the previous section (Guo et al., 2024). This framework indicates that carbon dioxide emissions per unit of economic output are typically measured as emissions per unit of GDP.

Third, this study includes 29 municipalities and provinces in China, excluding Tibet from the Southwest region and Xinjiang from the Northwest region. Hong Kong and Macao are also excluded. In 1949, China established six administrative regions (Hirata, 2024), a classification that has been widely adopted in empirical studies (e.g.,Yang et al. (2022). Accordingly, this study uses a categorical variable to classify provinces into six regional groups:

(a) North China: Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia.
(b) Northeast China: Liaoning, Jilin, and Heilongjiang.
(c) East China: Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong.
(d) South Central China: Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan.
(e) Southwest China: Sichuan, Guizhou, Yunnan, Tibet, and Chongqing.
(f) Northwest China: Shaanxi, Gansu, Qinghai, and Ningxia.

Fourth, the dataset spans the period from 2008 to 2021, capturing time-series dynamics. To account for temporal effects, the years are indexed from 1 to 14 and denoted as "SOL." Finally, detailed definitions and formulas for all variables are reported in Table AT1 in the Appendix.

Data analysis process

The data processing procedure was divided into three steps: (a) data preparation, (b) descriptive statistical analysis, and (c) GAMM estimation, which included multicollinearity assessment and cross-validation.

(1) Data Preparation:

This stage involved data cleaning and preprocessing. As described above, the dataset comprises observations from 29 municipalities and provinces in China over the period 2008 - 2021. Time is represented by the variable "SOL," which assigns integer values from 1 to 14 to each year. Furthermore, the 29 municipalities and provinces were classified into six designated regions: East China, North China, Northeast China, Northwest China, South Central China, and Southwest China, and coded from 1 to 6 accordingly. These assignments were treated as categorical variables.

(2) Descriptive Statistics:

Descriptive statistics, such as the mean, standard deviation, and range, were calculated for the green finance index, CDEI, and GDP. These statistics summarize the distributional characteristics and temporal and regional variations of the variables.

(3) Generalized additive mixed model analysis

The analysis of green finance and carbon emissions using the GAMM was implemented in R using the packages: "mgcv," "gamm4," "car," "caret," and "dplyr." The "mgcv" package was used to estimate generalized additive models (GAMs) and capture nonlinear relationships. While "gamm4" extended this framework by incorporating mixed-effects structures. The "car" package was used for regression diagnostics, including the assessment of multicollinearity using the variance inflation factor (VIF). The "caret" package facilitated model training and cross-validation, and "dplyr" supported data manipulation, including filtering, summarizing, and transformation. Collectively, these packages enabled efficient model estimation, diagnostic testing, and validation.

Accordingly, the GAMM analysis comprised three steps: (a) multicollinearity assessment, (b) model estimation, and (c) cross-validation.

(3.1) Multicollinearity assessment for variable selection

Before conducting the GAMM analysis, multicollinearity was assessed using variance inflation factors (VIFs). Multicollinearity refers to the extent to which independent variables in a regression model are highly correlated, which can affect the accuracy of the coefficient estimates and yield unreliable results (Hair et al., 2019). Variables with VIF values exceeding 5.00 were excluded from the model to mitigate these effects. VIF values above 5 indicate moderate multicollinearity, while values above 10 suggest severe multicollinearity (Hair et al., 2019). Therefore, a conservative threshold of 5.00 was adopted to enhance estimation accuracy and model stability.

(3.2) GAMM analysis

The GAMM was employed to analyze the relationship between green finance indices and the CDEI. The dependent variable is the CDEI, while the independent variables include green finance indices, GDP, SOL, and six regional categories. The model incorporates smooth terms for continuous covariates and categorical terms for regional classifications, enabling the flexible modeling of nonlinear relationships (Lin & Zhang, 1999; Wood, 2006, 2017). Model coefficients indicate the direction and magnitude of the effects: positive coefficients correspond to increases in the CDEI, whereas negative coefficients indicate decreases. Statistical significance is assessed using p-values; values below 0.05 are considered significant. The smooth terms capture nonlinear effects and are assessed through both p-values and graphical diagnostics (Lin & Zhang, 1999; Wood, 2017). The adjusted R^2 measures the proportion of variance in the CDEI explained by the model, while the deviance explained reflects the fraction of total variability accounted for by the fitted GAMM.

(3.3) Cross-validation for model evaluation

Cross-validation assesses the model's performance on data not used for estimation and reduces the risk of overfitting. The dataset was split into subsets, with the model trained on one part and tested on the other. Model performance was assessed using root mean squared error (RMSE) and R^2. RMSE measures the average squared difference between predicted and observed values, while R^2 measures the proportion of variance in the dependent variable explained by the model. Lower RMSE and higher R^2 values indicate better predictive and explanatory performance. The standard deviation of these metrics across subsets indicates the model's stability.

In this study, model fit was also evaluated using deviance explained and adjusted R^2 from the GAMM output. Residual summaries and diagnostic plots were used to inspect the distribution and scale of the residuals and identify outliers. Multicollinearity was controlled by screening covariates using the variance inflation factor (VIF) before estimation. Model robustness was assessed through repeated cross-validation with a 60% training and 40% testing split, and the mean and standard deviation of RMSE and R^2 across repetitions were used as performance indicators.

Analysis

This section consists of two parts: descriptive statistics and GAMM analysis, including multicollinearity assessment and cross-validation for model evaluation.

Descriptive statistics

Table 2 provides the descriptive statistics for the green financial-related variable indices and carbon emissions. The table lists the minimum, maximum, mean, and standard deviation of each variable. It also illustrates the range of these variables in green finance and carbon emissions, based on 406 observations.

However, as shown in Table 2, the green finance variables are expressed as percentages, whereas carbon emissions are measured in tons. Therefore, all variables were standardized, as shown in Table 3.

Furthermore, the six regions and the 14-year time series were treated as categorical variables, each represented by a unique numeric code. For instance, the number 1 represents the year 2008, while in the regional classification, the number 1 corresponds to North China, which includes Beijing Municipality, Tianjin Municipality, Hebei, Shanxi, and Inner Mongolia.

Regarding the temporal evolution of each variable, Figures 1-8 illustrate the time-series trends across the different regions. For instance, Figure 1 depicts CDEI across six regions over time.

Figure 1 shows trends in CDEI across various regions of China from 2008 to 2021. North China exhibits a steady increase in emission intensity, whereas East and Northeast China show gradual declines. Emissions in Northwest China remain relatively stable, with only minor fluctuations, while South Central and Southwest China show consistent decreases. Overall, the figure highlights clear regional heterogeneity in emission trends, with some areas experiencing reductions and others showing increases.

Figures 2–8 illustrate the time-series evolution of green financial indices and GDP across different regions of China from 2008 to 2021. All regions exhibit a consistent upward trend in green finance indicators, including green credit, green bonds, green insurance, and green investment, although growth rates vary. East and North China show significant increases, whereas South Central and Southwest China experience moderate growth.

In addition, Figure 8 shows that GDP displays a sustained upward trend across all regions, with East China recording the highest growth, followed by North China and the remaining regions. These trends reflect substantial progress in both green financial development and economic growth during the study period.

Generalized additive mixed model analysis

The GAMM analysis involved four steps: (a) assessing multicollinearity using VIF and correlation analysis, (b) specifying the GAMM formulation, (c) conducting residual diagnostics and evaluating random and fixed effects, and (d) performing cross-validation, with deviance explained and adjusted R^2 calculated as performance metrics.

The first step is essential, as multicollinearity among explanatory variables can adversely affect model accuracy. To assess this, VIF values were computed to quantify the extent to which the other variables explain variance in a given variable. Table 4 presents the initial VIF values, indicating potential multicollinearity. Green insurance exhibits the highest VIF (15.668), followed by green investment (12.250), suggesting substantial multicollinearity. Green bonds also display a moderately high VIF (5.747). In contrast, the remaining variables, including green credit, green support, green funds, and GDP, show low VIF values ranging from 0.041 to 1.176, indicating minimal multicollinearity.

Table 2. Descriptive Statistics of Green Financial Variables and Carbon Dioxide Emission Intensity

Variable	Minimum	Maximum	Mean	Std. Deviation
Green Credit	0.029	0.052	0.040	0.005
Green Investment	0.046	0.079	0.062	0.008
Green Insurance	0.058	0.097	0.076	0.010
Green Bonds	0.091	0.152	0.120	0.015
Green Support	0.012	0.026	0.018	0.003
Green Funds	0.041	0.072	0.054	0.007
Green Equity	0.045	0.080	0.062	0.008
GDP	1018.579	125618.503	24462.345	21261.699
CDEI	0.319	8.629	2.365	1.770

Table 3. Standardized Variables of Green Financial Instrument and Carbon Dioxide Emission Intensity

Variable	Minimum	Maximum	Mean	Std. Deviation
Green Credit	-2.069	2.318	0.000010	0.999998
Green Investment	-2.027	2.279	0.000010	0.999979
Green Insurance	-1.912	2.168	-0.000010	1.000023
Green Bonds	-1.950	2.175	-0.000010	1.000028
Green Support	-2.103	2.520	0.000000	1.000023
Green Funds	-1.941	2.547	0.000030	1.000001
Green Equity	-2.141	2.343	0.000000	1.000006
GDP	-1.103	4.758	-0.000010	1.000031
CDEI	-1.156	3.539	0.000000	0.999993

The correlation analysis presented in Table 5 supports these observations. Moderate negative correlations exist between the CDEI and variables such as GDP (-0.436), green equity (-0.270), and green bonds (-0.267). These results suggest that, although some variables show signs of multicollinearity, others display weak or moderate associations with the CDEI, indicating a more varied influence of green financial indices on carbon emissions.

After excluding variables with high VIF values, the final VIF results are presented in Table 6. These results show that green credit, green support, green funds, and GDP have low VIF scores, indicating they are suitable for further analysis. Moreover, Table 7 indicates that the remaining variables exhibit acceptable correlation levels, allowing the GAMM estimation to proceed to explore their relationships with the CDEI.

Second, the GAMM specification adopts CDEI as the dependent variable. The independent variables include green credit (GC), green support (GS), green funds (GF), GDP, and six regional areas of China. Smooth terms are applied to continuous variables, allowing the model to capture nonlinear relationships, while regional areas are treated as categorical variables. As shown in the formula below, ZGC, ZGS, ZGF, ZGDP, and SOL are modeled using smooth functions denoted by *s (·)*.

Formula = ZCDEI ~ s(ZGC) + s(ZGS) + s(ZGF) + s(ZGDP) + s(SOL) + Area

In scalar form, the GAMM for the province in year can be written as,

$$g(E[ZCDEI_{it}])=\beta_0+f_1(ZGC_{it})+f_2(ZGS_{it})+f_3(ZGF_{it})+f_4(ZGDP_{it})+f_5(SOL_t)+\alpha_{r(i)}+\varepsilon_{it},$$

Table 4. The Initial Step of Multicollinearity Analysis

Variable	VIF
Green Credit	0.081
Green Investment	12.250
Green Insurance	15.668
Green Bonds	5.747
Green Support	0.041
Green Funds	0.903
Green Equity	2.192
GDP	1.176

where denotes the identity link function, are smooth functions of the standardized covariates, and represents the fixed effect for the region . The index denotes province, denotes year, and indicates the region to which the province belongs. The error term is assumed to follow a normal distribution with mean zero and variance .

Tables 8 and 9 summarize the influence of regional factors and other variables on the CDEI. In Table 8, East China serves as the reference region in the GAMMs analysis, with a beta coefficient of 0.00. The results show that East, North, Northeast, and Northwest China have significant effects on CDEI, whereas South Central and Southwest China do not.

Table 8 also shows that the model accounts for 67.59% of the data variability, as measured by deviance explained. The adjusted R^2 value of 0.6617 indicates that approximately 66.17% of the variance in the CDEI is accounted for by the model.

Table 9 presents the significance of the smooth terms in the GAMMs analysis. GDP exhibits a significant nonlinear effect on CDEI, with an F statistic of 10.173 and a *p*-value of 0.001 or less, indicating a strong influence. In contrast, green credit, green support, and green funds do not significantly affect CDEI, as their p-values exceed 0.05. The time-series variable (SOL) also shows no significant effect ($p = 0.666$). Overall, GDP is the only variable with a statistically significant impact on CDEI in this analysis.

Figure 9 illustrates the nonlinear effect of GDP on CDEI. As GDP increases, its impact on CDEI decreases and stabilizes at higher levels, suggesting that further economic growth alone is unlikely to raise CDEI once a certain level is reached. This stabilization implies that additional measures beyond economic growth may be required to achieve further reductions.

Figure 10 presents the parametric coefficients for the regional impacts on CDEI, with East China serving as the reference region with a beta coefficient of 0.00, as shown in Table 8. North, Northeast, and Northwest China exhibit significant positive effects on the CDEI, as indicated by higher estimates and significance levels. In contrast, South Central and Southwest China show minimal and non-significant impacts. These results highlight the pronounced influence of regional factors, with North, Northeast, and Northwest China associated with higher carbon emissions, whereas South Central and Southwest China have a limited impact.

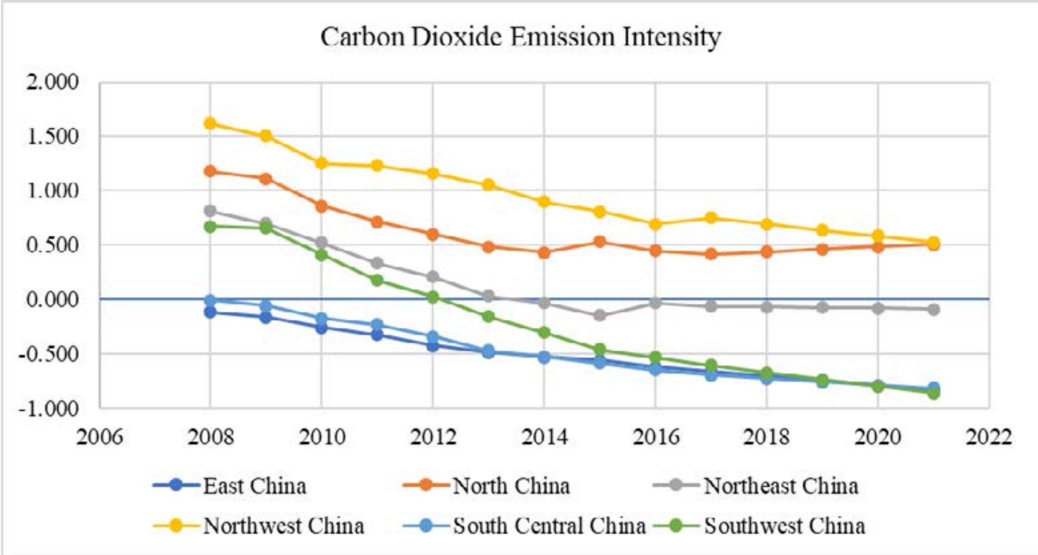

Fig. 1. The Carbon Dioxide Emission Intensity by Year

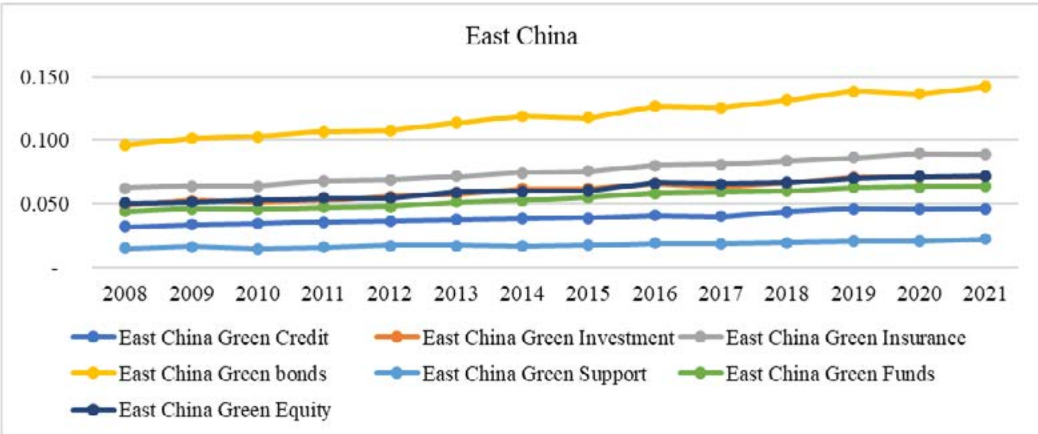

Fig. 2. The Time-Based Evolution of Green Financial Indexes in the East China Region

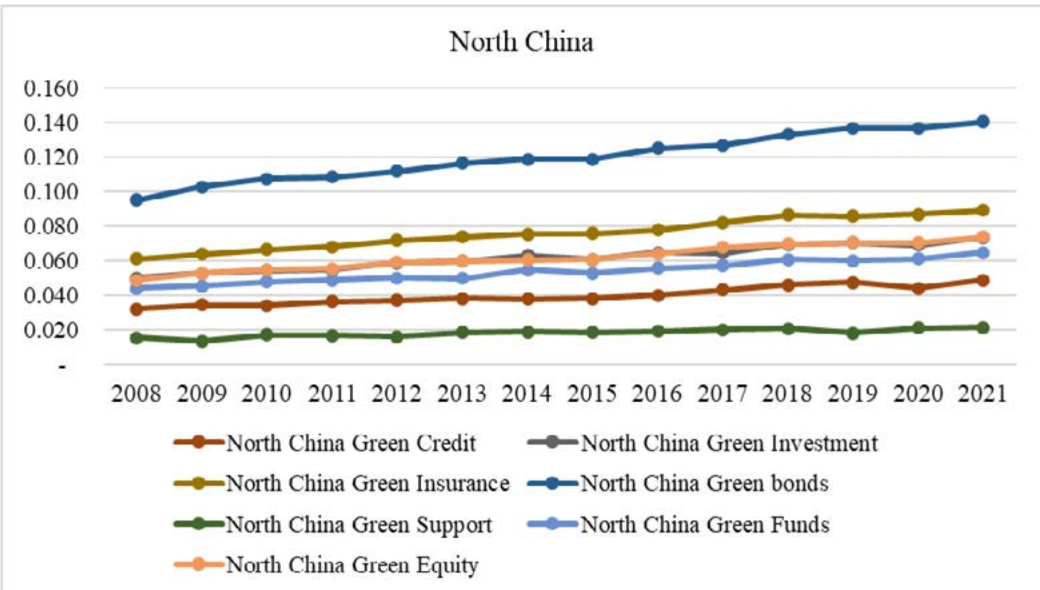

Fig. 3. The Time-Based Evolution of Green Financial Indexes in the North China Region

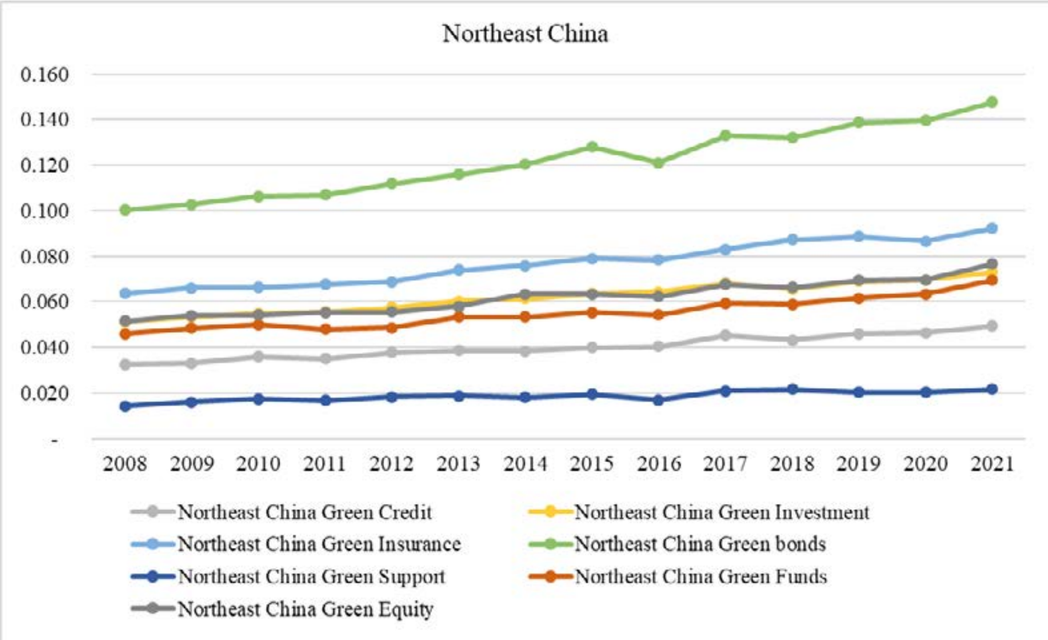

Fig. 4. The Time-Based Evolution of Green Financial Indexes in the Northeast China Region

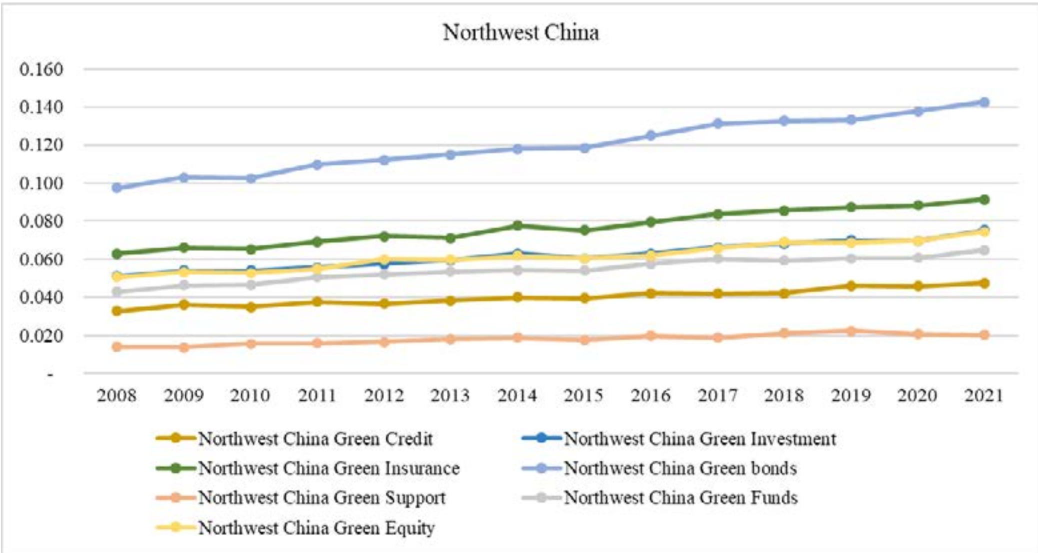

Fig. 5. The Time-Based Evolution of Green Financial Indexes in the Northwest China Region

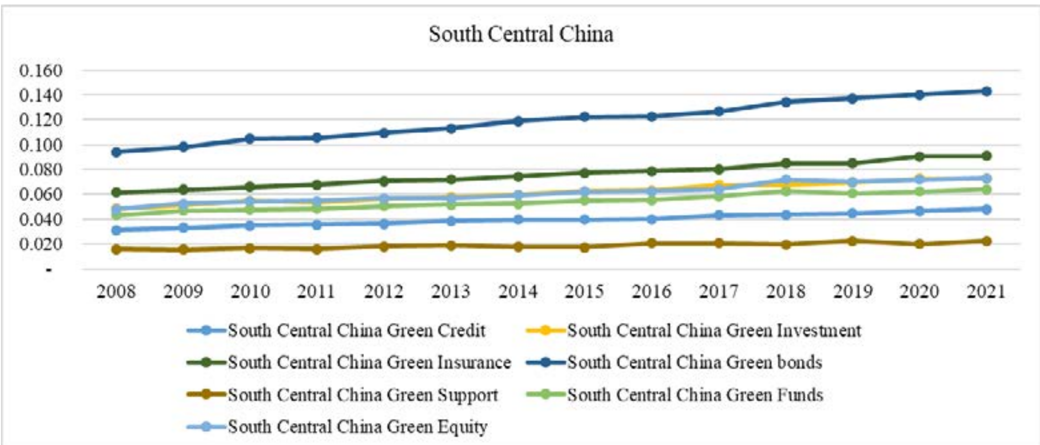

Fig. 6. The Time-Based Evolution of Green Financial Indexes in the South Central China Region

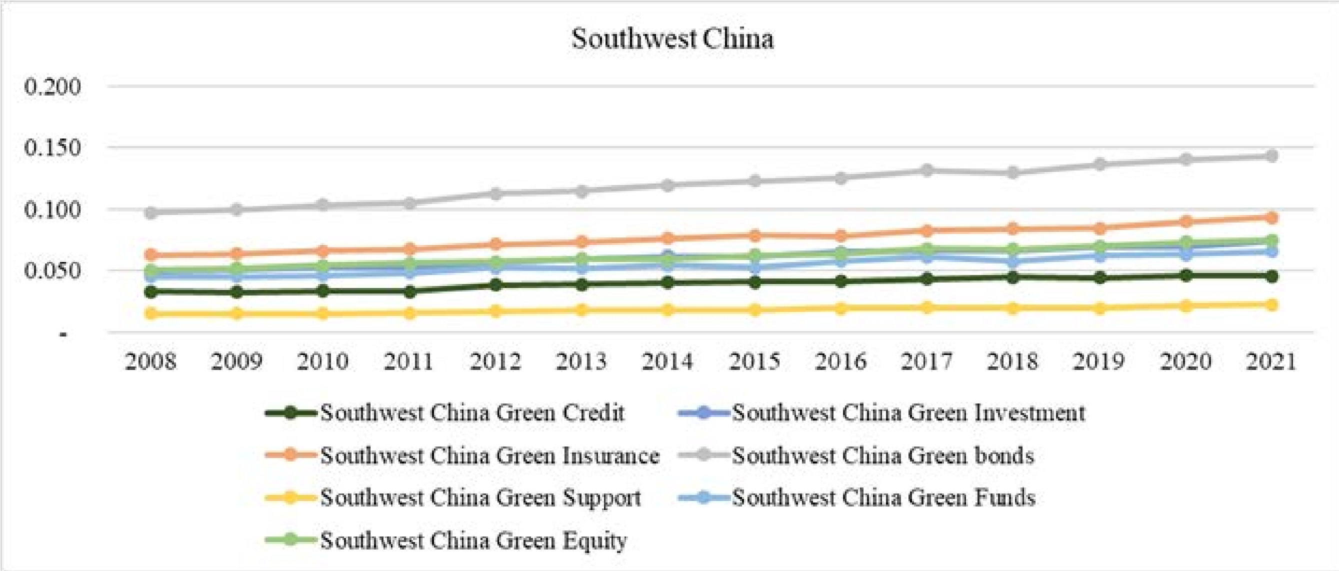

Fig. 7. The Time-Based Evolution of Green Financial Indexes in the Southwest China Region

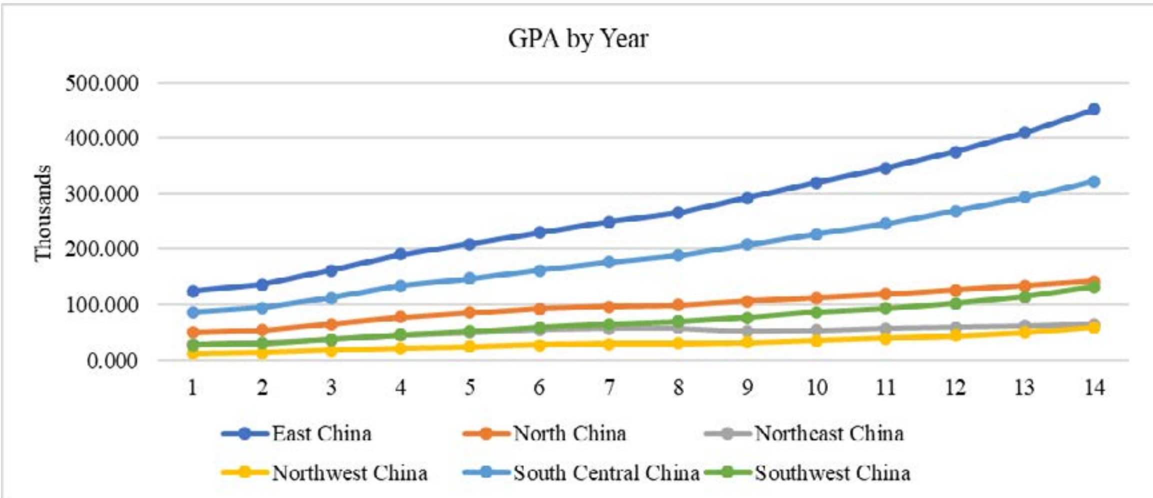

Fig. 8. Figure 8. The Six Regions' GDP by Year

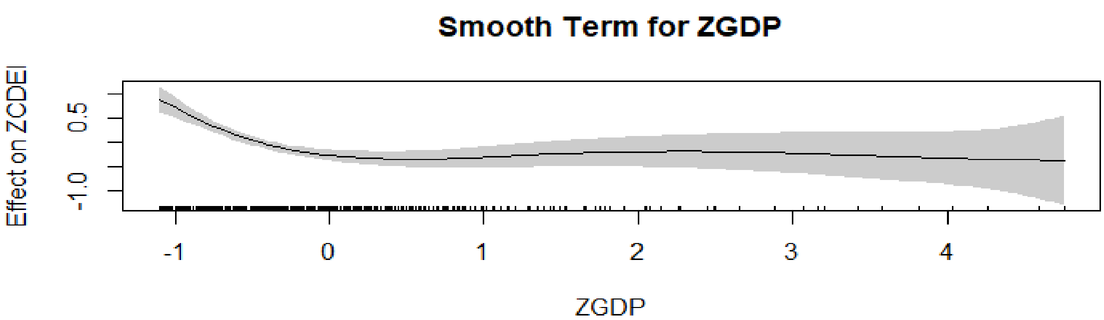

Fig. 9. Tinear Impact of GDP on CDEI

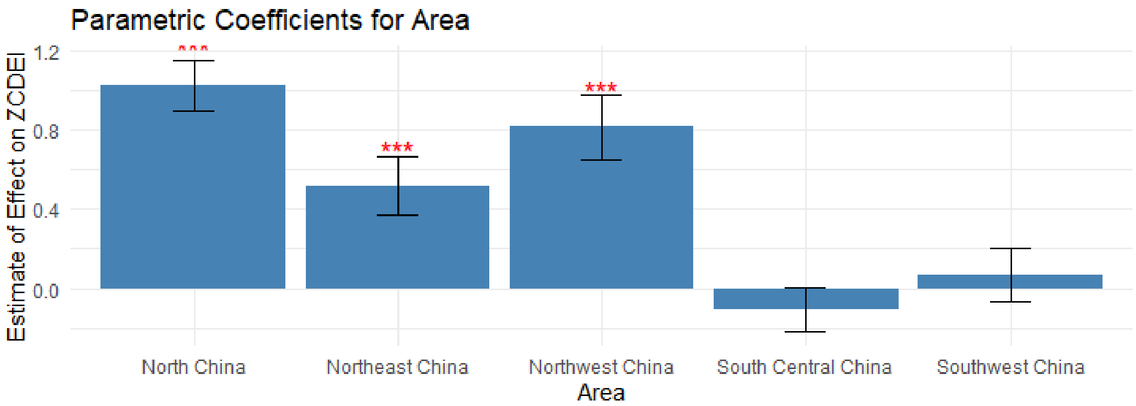

Fig. 10. Regional Effects on Carbon Dioxide Emission Intensity

Third, these results include the residual distribution and random and fixed effects to assess the accuracy and robustness of the GAMM.

Table 10 displays the scaled residuals from the mixed-effects model, showing their range and distribution. The minimum residual was -2.312, indicating the largest negative error, while the maximum was 3.445, representing the largest positive error. The median residual was close to zero (-0.073), suggesting that the model's predictions were generally accurate. The first quartile (-0.433) and third quartile (0.298) show that most residuals fall within a narrow range, suggesting only minor deviations from the observed values. In conclusion, Table 10 demonstrates that the model effectively captured the relationships among the variables, with most residuals close to zero. Although a few extreme values were observed, the majority of errors were small, indicating a strong overall model fit.

In Table 11, SOL represents the time-series variable included in the multicollinearity assessment. Its variance was 0.000, indicating no random variation over time. This suggests that the time-series component does not contribute significantly to the model. In contrast, other variables, such as green funds and GDP, exhibit non-zero variances, indicating they explain random variation, whereas SOL shows no significant random effects.

Table 12 presents the fixed-effects estimates from the model, showing the effects of regional and time-series variables on the dependent variable. North, Northeast, and Northwest China exhibit significant positive effects, whereas South Central and Southwest China do not. Among the smooth terms, only GDP (Xs(GDP)Fx1) shows a significantly negative effect. In contrast, other variables, such as green credit, green support, and the time series component (SOL), do not show significant effects in the model.

Table 13 shows the correlations between the fixed effects of the model. Strong negative correlations are observed between the intercept and regional variables, such as North China (-0.688), Northeast China (-0.611), and Northwest China (-0.677), highlighting significant regional differences. Among the smooth terms, GDP (Xs(ZGDP)Fx1) exhibits moderate

Table 5. Correlation Analysis for these Variables at the Initial Step

Variable	CDEI	Green Credit	Green Investment	Green Insurance	Green Bonds	Green Support	Green Funds	Green Equity	GDP
CDEI	1								
Green Credit	-0.244	1							
Green Investment	-0.256	0.886	1						
Green Insurance	-0.258	0.893	0.938	1					
Green Bonds	-0.267	0.909	0.952	0.960	1				
Green Support	-0.201	0.635	0.678	0.707	0.699	1			
Green Funds	-0.264	0.863	0.913	0.927	0.944	0.689	1		
Green Equity	-0.270	0.882	0.928	0.939	0.952	0.679	0.916	1	
GDP	-0.436	0.333	0.374	0.374	0.379	0.288	0.364	0.374	1

Table 7. Analysis for these Variables at the Final Step

Variable	CDEI	Green Credit	Green Support	Green Funds	GDP
CDEI	1				
Green Credit	-0.244	1			
Green Support	-0.201	0.635	1		
Green Funds	-0.264	0.863	0.689	1	
GDP	-0.436	0.333	0.288	0.364	1

correlations with other variables, such as North China (0.203), indicating its influence across regions. However, green credit (Xs(ZGC)Fx1), green support (Xs(ZGS)Fx1), and green funds (Xs(ZGF)Fx1) show weak correlations with other terms, implying minimal interaction with regional factors. The time-series variable (Xs(SOL)Fx1) also demonstrates weak correlations with most variables, suggesting a limited impact on the model's fixed effects. Overall, regional factors and GDP exert a stronger influence than other variables.

Fourth, for model evaluation, this study employed repeated cross-validation, deviance explained, and adjusted R^2, using 60% of the data for training and 40% for testing across 10 repetitions.

Table 14 shows that across these 10 iterations, the model achieved a mean RMSE of 0.7636 and a standard deviation of 0.0471, indicating that the average prediction error was approximately 0.76 units with little variation across repeats. The mean R^2 was 0.3863 (SD= 0.056), indicating that the model explained roughly 38.6% of the variance in the dependent variable. While the low RMSE indicates that the model performs well in terms of prediction error, the moderate R^2 indicates that a substantial portion of the variance remains unexplained, suggesting room for further improvement. Therefore, the model demonstrated reasonable predictive accuracy but could be refined to enhance its explanatory power. Table 14. Cross-validation for 60% of the training data

Conclusion

This study examined the relationships among green finance instruments, GDP, and the CDEI in China using the GAMM. Green finance in this study includes green credit, green support, and green funds. The analysis covered time-series data from 2008 to 2021 (SOL) for 29 provinces and municipalities grouped into six regions in China. The results yield two main findings regarding green finance and emissions control.

First, the GAMMs showed significant regional differences in the CDEI across China. North, Northeast, and Northwest China showed significant increases in the CDEI, driven by economic activities and carbon emissions. In contrast, South Central China and Southwest China displayed minimal impact on the CDEI, indicating lower emission contributions than East China, the reference region. The findings demonstrate that regional economic activities and GDP influence environmental impacts, with specific areas showing higher emissions due to their industrial activity.

Second, the analysis of smooth terms in the GAMM indicates that GDP is a key determinant of the CDEI. However, green credit, support, and funds showed no significant effect on reducing the CDEI between 2008 and 2021. The findings indicate that while economic growth drives emissions, the current application of green finance instruments may be insufficient for significant emission mitigation. The findings indicate that GPD has a significant impact on environmental outcomes and that stronger strategies or more effective green finance instruments are important.

Table 6. The Final Step of Multicollinearity Analysis

Variable	VIF
Green Credit	0.975
Green Support	0.934
Green Funds	0.599
GDP	1.157

Discussion

The differences in findings regarding the impact of green finance instruments on the CDEI may partly be attributable to variations in analytical approaches. This study applies GAMMs to identify complex relationships among variables in a time-series and nonlinear dataset. In contrast, other studies reviewed in the literature often use regression models and GMM, which may not capture nonlinear interactions as effectively (Fan et al., 2024; Zhang et al., 2024). GAMM can reveal trends and patterns across regions and over time that linear models may not capture. In particular, smooth nonlinear terms capture the flexible effects of covariates on the CDEI, while regional effects more clearly represent unobserved regional heterogeneity than linear or spatial models that rely solely on fixed intercepts and predefined spatial structures.

Furthermore, this study focuses on specific green finance instruments, namely, green credit, support, and funds, whereas broader analyses in the literature also consider green credit, bonds, investment, insurance, support, and securities (Cui et al., 2024; Liu et al., 2024; Zhang et al., 2024; Zhou et al., 2024). However, Fan et al. (2024) report that green insurance, support, and equity do not affect the CDEI. This limited scope may restrict the observed impact of green finance on the CDEI, thereby contributing to the variation in findings. Expanding the range of green finance indicators could provide a more comprehensive understanding of their effects on the CDEI.

Table 8. GAMMs Coefficients for Regional Impact

Variable	beta (β) coefficient	Std. Error	t value	p value
(Intercept)	-0.32949	0.08425	-3.911	0.000***
North China	1.02705	0.12692	8.092	0.000***
Northeast China	0.51632	0.14929	3.459	0.001**
Northwest China	0.81492	0.16186	5.035	0.000***
South Central China	-0.10783	0.11381	-0.947	0.344
Southwest China	0.06457	0.13574	0.476	0.635

Table 9. Significance of Smooth Terms in GAMMs

Variable	Effective Degrees of Freedom	Reference Degrees of Freedom	F Statistic	p value
s(Green Credit)	1.000	1.000	0.625	0.430
s(Green Support)	1.000	1.000	0.000	0.997
s(Green Funds)	1.682	1.682	0.392	0.612
s(GDP)	4.794	4.794	10.173	0.000***
s(SOL)	1.000	1.000	1.187	0.666

Table 10. Scaled Residuals Summary

Min	1Q	Median	3Q	Max
-2.312	-0.433	-0.073	0.298	3.445

Table 11. Random Effect

Group	Name	Variance	Std. Dev.
Xr	s(Green Credit)	0.000	0.000
Xr.0	s(Green Support)	0.000	0.000
Xr.1	s(Green Funds)	0.053	0.231
Xr.2	s(GDP)	5.724	2.393
Xr.3	s(SOL)	0.000	0.000
Area	(Intercept)	0.000	0.000
	Residual	0.550	0.742

Table 12. Fixed Effects Estimates for Regional and Variable Impact

Variable	Estimate	Std. Error	t-value
X(Intercept)	-0.329	0.084	-3.911
XArea North China	1.027	0.127	8.092
XArea Northeast China	0.516	0.149	3.459
XArea Northwest China	0.815	0.162	5.035
XArea South Central China	-0.108	0.114	-0.947
XArea Southwest China	0.065	0.136	0.476
Xs(Green Credit)Fx1	0.074	0.094	0.790
Xs(Green Support)Fx1	0.000	0.053	-0.004
Xs(Green Funds)Fx1	0.033	0.146	0.228
Xs(GDP)Fx1	-0.829	0.329	-2.517
Xs(SOL)Fx1	0.069	0.160	0.432

Table 13. Correlation of Fixed Effects

	X(Int)	XArNrthCh	XArNrthsC	XArNrthwC	XArSCC	XArStC	X(ZGC)	X(ZGS)	X(ZGF)	X(ZGDP)
XArNrthChn	-0.688									
XArNrthstCh	-0.611	0.453								
XArNrthwstC	-0.677	0.432	0.4							
XArSthCntrC	-0.679	0.448	0.388	0.437						
XArSthwstCh	-0.671	0.476	0.432	0.468	0.435					
Xs(Green Credit)Fx1	-0.012	0.028	-0.007	0.012	0.019	-0.012				
Xs(Green Support)Fx1	0.045	-0.05	-0.029	0.013	-0.097	-0.015	-0.048			
Xs(Green Funds)Fx1	0.045	-0.08	-0.01	-0.044	-0.016	-0.029	0.054	0.054		
Xs(GDP)Fx1	-0.063	-0.011	-0.019	0.203	0.041	0.02	0.036	-0.019	-0.055	
Xs(SOL)Fx1	-0.091	0.096	0.078	0.111	0.01	0.088	-0.602	0.208	-0.608	0.048

The study further indicates that North, Northeast, and Northwest China significantly affect the CDEI, whereas South Central and Southwest China show no significant effects. Although these regions are all considered developing, regional economic development and GDP growth contribute to higher CDEI levels in North, Northeast, and Northwest China.

These findings contrast with those of Lian et al. (2024) and Liu et al. (2022), who report different effects of green finance on CDEI. Lian et al. (2024) find that green finance instruments, such as green credit, investment, insurance, bonds, support, and funds, positively affect energy development in Beijing and Shanghai but have no significant impact in Northern and Western China. Meanwhile, Liu et al. (2022) identify GDP growth and population increases as the primary drivers of rising carbon emissions in major cities such as Beijing, Tianjin, Shanghai, and Chongqing, while improvements in industrial and energy structures contribute to reductions in emissions.

In conclusion, these methodological differences demonstrate how model selection can influence data interpretation and conclusions regarding the impact of green finance instruments. While regression-based analyses provide insights into direct relationships, GAMMs allow for a more nuanced examination of how categorical, temporal, and nonlinear factors interact within a model. This methodological advantage may explain why the results of this study differ from those in the literature that use simpler models or broader ranges of variables.

Implementation

This study identifies significant regional impacts of green finance on the CDEI in North, Northeast, and Northwest China, where economic activities contribute to higher carbon emissions. Businesses in these regions are encouraged to adjust their investment strategies toward green finance programs that support renewable energy and energy efficiency, thereby reducing environmental impacts while gaining access to financial incentives. Furthermore, financial institutions should develop tailored financial products that reflect the specific economic and environmental contexts of these regions to enhance investment attractiveness and ensure regulatory compliance.

Table 14. Cross-validation for 60% of Training Data

	Mean	SD
RMSE	0.764	0.047
R^2	0.386	0.056

Research limitations and recommendations for future studies

This study has limitations in both scope and methodology, as it focuses on a limited selection of green finance instruments and a study period that may not adequately capture the long-term effects of these measures on the CDEI. Therefore, future research should expand the range of green finance instruments examined and extend the study period to better assess their sustainability and effectiveness over time better. Moreover, broadening the geographical scope beyond China could yield insights relevant to diverse economic and regulatory contexts, thereby improving the generalizability of the findings and deepening our understanding of how green finance can support sustainable development.

Reference

Ante, L. (2024). The scope of green finance research: Research streams, influential works and future research paths. *Ecological Economics*, *224*, 108302. https://doi.org/10.1016/j.ecolecon.2024.108302

Augustin, N. H., Trenkel, V. M., Wood, S. N., & Lorance, P. (2013). Space-time modelling of blue ling for fisheries stock management. *Environmetrics*, *24*(2), 109–119. https://doi.org/10.1002/env.2196

Bai, J., Chen, Z., Yan, X., & Zhang, Y. (2022). Research on the impact of green finance on carbon emissions: evidence from China. *Economic Research-Ekonomska Istrazivanja*, *35*(1), 6965–6984. https://doi.org/10.1080/1331677X.2022.2054455

Banerjee, A. K., Boubaker, S., & Al-Nassar, N. S. (2024). Climate policy initiatives, green finance, and carbon risk interconnectedness. *Finance Research Letters*, *67*, 105776. https://doi.org/10.1016/j.frl.2024.105776

Brown-Schmidt, S., Cho, S. J., Fenn, K. M., & Trude, A. M. (2025). Modeling spatio-temporal patterns in intensive binary time series eye-tracking data using Generalized Additive Mixed Models. *Brain Res*, *1854*, 149511. https://doi.org/10.1016/j.brainres.2025.149511

Cissoko, M., Sagara, I., Guindo, A., Maiga, M., Dembele, P., Bationo, C. S., . . . Gaudart, J. (2025). Impact of control interventions on Malaria incidence in the general population of Mali. *J Epidemiol Glob Health*, *15*(1), 40. https://doi.org/10.1007/s44197-025-00381-2

Cui, X., Mohd Said, R., Abdul Rahim, N., & Ni, M. (2024). Can green finance lead to green investment? Evidence from heavily polluting industries. *International Review of Financial Analysis*, *95*, 103445. https://doi.org/10.1016/j.irfa.2024.103445

Ding, J. (2024). A study of the effects of regional competition and digital financial inclusion on urban carbon emissions. *Academic Journal of Business & Management*, *6*(8), 250–255. https://doi.org/DOI: 10.25236/AJBM.2024.060837

Fan, L., Peng, B., Lin, Z., Zou, H., & Du, H. (2024). The effects of green finance on pollution and carbon reduction: Evidence from China's industrial firms. *International Review of Economics & Finance*, *95*, Article 103490. https://doi.org/10.1016/j.iref.2024.103490

Fan, Y., Anwar, S., & Long, R. (2025). Navigating economic policy uncertainty: The role of ESG performance in mitigating the risk of nonfinancial firms in China. *Economics & Politics*. https://doi.org/10.1111/ecpo.12352

Feng, C. (2022). Spatial-temporal generalized additive model for modeling COVID-19 mortality risk in Toronto, Canada. *Spat Stat*, *49*, 100526. https://doi.org/10.1016/j.spasta.2021.100526

Ferrari, C., Evangelista, C., Basirico, L., Castellani, S., Biffani, S., & Bernabucci, U. (2025). Application of a generalized additive mixed model in time series study of dairy cow behavior under hot summer conditions. *J Dairy Sci*, *108*(2), 1554–1572. https://doi.org/10.3168/jds.2024-25001

Ferrari, C., Evangelista, C., Basiricò, L., Castellani, S., Biffani, S., & Bernabucci, U. (2025). Application of a generalized additive mixed model in time series study of dairy cow behavior under hot summer conditions. *Journal of Dairy Science*, *108*(2), 1554–1572. https://doi.org/10.3168/jds.2024-25001

Guo, Q., Wang, H., Lu, X., & Qu, L. (2024). Effects of innovation environment on carbon intensity: The moderating role of information industry. *International Review of Economics & Finance*, *92*, 967–977. https://doi.org/10.1016/j.iref.2024.02.059

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Cengage.

Hirata, K. (2024). Socialist Industrialization as a Hybrid System, 1948–1957. In K. Hirata (Ed.), *Making Mao's Steelworks: Industrial Manchuria and the Transnational Origins of Chinese Socialism* (pp. 99–226). Cambridge University Press. https://doi.org/DOI: 10.1017/9781009382281.006

Huang, L. (2024). Green bonds and ESG investments: Catalysts for sustainable finance and green economic growth in resource-abundant economies. *Resources Policy*, *91*, 104806. https://doi.org/10.1016/j.resourpol.2024.104806

Li, Y., & Xu, Y. (2024). Impact of green finance on China's pollution reduction and carbon efficiency: Based on the spatial panel model. *International Review of Economics & Finance*, *94*, 103382. https://doi.org/10.1016/j.iref.2024.103382

Lian, Y., Shang, Y., & Qian, F. (2024). Spatial effects of green finance development in Chinese provinces under the context of high-quality energy development. *Economic Change and Restructuring*, *57*(2), Article 23. https://doi.org/10.1007/s10644-024-09600-5

Liang, Z., & Yang, X. (2024). The impact of green finance on the peer effect of corporate ESG information disclosure. *Finance Research Letters*, *62*, Article 105080. https://doi.org/10.1016/j.frl.2024.105080

Lin, X., & Zhang, D. (1999). Inference in generalized additive mixed models by using smoothing splines. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, *61*(2), 381–400. http://www.jstor.org/stable/2680648

Liu, X., Cui, J., Wu, Y., Yue, X., Shen, J., & Guo, P. (2024). The nexus between green finance and carbon emissions: Evidence from maturity mismatch in China. *Sustainability*, *16*(10), Article 4319. https://doi.org/10.3390/su16104319

Liu, Y., Jiang, Y., Liu, H., Li, B., & Yuan, J. (2022). Driving factors of carbon emissions in China's municipalities: a LMDI approach. *Environmental Science and Pollution Research*, *29*(15), 21789–21802. https://doi.org/10.1007/s11356-021-17277-w

Liu, Y., Zhao, X., Liu, Y., & Kong, F. (2023). The dynamic impact of digital economy on the green development of traditional manufacturing industry: Evidence from China. *Economic Analysis and Policy*, *80*, 143–160. https://doi.org/https://doi.org/10.1016/j.eap.2023.08.005

Lv, K., Fan, Y., & Cheng, Y. (2024). How does regional integration affect CO2 emission intensity? A natural experiment based on the expansion of the Yangtze River Delta, China. *The Annals of Regional Science*, *73*(2), 493–519. https://doi.org/10.1007/s00168-024-01264-3

Mohy-ud-Din, K., Shahbaz, M., & Khamdamov, S. J. (2025). Does green governance reflect corporate sustainability performance? New insight from G5 countries. *Corporate Social Responsibility and Environmental Management*, *n/a*(n/a). https://doi.org/10.1002/csr.3203

Nelder, J. A., & Wedderburn, R. W. M. (1972). Generalized linear models. *Journal of the Royal Statistical Society. Series A (General)*, *135*(3), 370–384. https://doi.org/10.2307/2344614

Nepal, R., Zhao, X., Liu, Y., & Dong, K. (2024). Can green finance strengthen energy resilience? The case of China. *Technological Forecasting and Social Change*, *202*, 123302. https://doi.org/10.1016/j.techfore.2024.123302

Pedersen, E. J., Miller, D. L., Simpson, G. L., & Ross, N. (2019). Hierarchical generalized additive models in ecology: An introduction with mgcv. *PeerJ*, *7*, e6876. https://doi.org/10.7717/peerj.6876

Ruppert, D., Wand, M. P., & Carroll, R. J. (2010). *Semiparametric Regression*. Cambridge University Press. https://doi.org/10.1017/cbo9780511755453

Safi, A., Kchouri, B., Elgammal, W., Nicolas, M. K., & Umar, M. (2024). Bridging the green gap: Do green finance and digital transformation influence sustainable development? *Energy Economics*, *134*, 107566. https://doi.org/10.1016/j.eneco.2024.107566

Sharma, S. S. (2011). Determinants of carbon dioxide emissions: Empirical evidence from 69 countries. *Applied Energy*, *88*(1), 376–382. https://doi.org/10.1016/j.apenergy.2010.07.022

Stram, D. O., & Lee, J. W. (1994). Variance components testing in the longitudinal mixed effects model. *Biometrics*, *50*(4), 1171–1177. https://doi.org/10.2307/2533455

Susan, E. B., & Pan, Y. (2024). Trust as a determinant of green finance through information sharing and technological penetration: Integrating the moderation of governance for sustainable growth. *Technology in Society*, *77*, 102565. https://doi.org/10.1016/j.techsoc.2024.102565

Tufail, M., Song, L., & Khan, Z. (2024). Green finance and green growth nexus: evaluating the role of globalization and human capital. *Journal of Applied Economics*, *27*(1), 2309437. https://doi.org/10.1080/15140326.2024.2309437

van Niekerk, A. J. (2024). Economic Inclusion: Green Finance and the SDGs. *Sustainability*, *16*(3), 1128. https://www.mdpi.com/2071-1050/16/3/1128

Wang, C., Wang, L., Zhao, S., Yang, C., & Albitar, K. (2024). The impact of Fintech on corporate carbon emissions: Towards green and sustainable development. *Business Strategy and the Environment*, *33*(6), 5776–5796. https://doi.org/10.1002/bse.3778

Wang, J., Mishra, S., Sharif, A., & Chen, H. (2024). Dynamic spillover connectedness among green finance and policy uncertainty: Evidence from QVAR network approach. *Energy Economics*, *131*, Article 107330. https://doi.org/10.1016/j.eneco.2024.107330

Wang, J., Tian, J., Kang, Y., & Guo, K. (2023). Can green finance development abate carbon emissions: Evidence from China. *International Review of Economics & Finance*, *88*, 73–91. https://doi.org/10.1016/j.iref.2023.06.011

Wei, N. (2024). Green finance, market integration, and regional economic resilience. *Finance Research Letters*, *67*, Article 105777. https://doi.org/10.1016/j.frl.2024.105777

Wong, W. M., & Su, W. (2025). Air pollution and health burden: a generalized additive mixed model approach to PM2.5, life Expectancy, and respiratory infections and tuberculosis in Thailand, Malaysia, and Singapore. *Air Quality, Atmosphere & Health*. https://doi.org/10.1007/s11869-025-01872-8

Wong, W. M., Tzeng, S.-Y., Mo, H.-F., & Su, W. (2024a). Impact of COVID-19 on PM2.5 concentrations in Singapore, Indonesia, and Thailand: Cluster Analysis and Generalized Additive Mixed Models. *Archives of Environmental Protection*, *50*(4), 116–1236. https://doi.org/10.24425/aep.2024.152901

Wong, W. M., Tzeng, S.-Y., Mo, H.-F., & Su, W. (2024b). Predicting air quality trends in Malaysia's largest cities: the role of urban population dynamics and COVID-19 effects. *Archives of Environmental Protection*, *50*(2), 65–74. https://doi.org/10.24425/aep.2024.150553

Wood, S. N. (2006). Low-rank scale-invariant tensor product smooths for generalized additive mixed models. *Biometrics*, *62*(4), 1025–1036. https://doi.org/10.1111/j.1541-0420.2006.00574.x

Wood, S. N. (2017). *Generalized Additive Models*. Chapman and Hall/CRC. https://doi.org/10.1201/9781315370279

Xie, P., Lu, Y., & Xie, Y. (2024). The Influencing Factors of Carbon Emissions in the Industrial Sector: Empirical Analysis Based on a Spatial Econometric Model. *Sustainability*, *16*(6), Article 2478. https://doi.org/10.3390/su16062478

Xue, H., & Kan, L. (2024). Measurement and evaluation of the development level of green finance in Western China. *Journal of Entrepreneurship in Science and Technology*, *37*(3). https://qikan.cqvip.com/Qikan/Article/Detail?id=7111674961&from=Qikan_Article_Detail

Yang, B., Bai, Z., & Wang, J. (2022). Spatiotemporal dynamic differences of energy-related CO2 emissions and the related driven factors in six regions of China during two decades. *Environmental Science and Pollution Research*, *29*(17), 24737–24756. https://doi.org/10.1007/s11356-021-17482-7

Yu, B., Liu, L., & Chen, H. (2023). Can green finance improve the financial performance of green enterprises in China? *International Review of Economics & Finance*, *88*, 1287–1300. https://doi.org/10.1016/j.iref.2023.07.060

Zairis, G., Liargovas, P., & Apostolopoulos, N. (2024). Sustainable finance and ESG importance: A systematic literature review and research agenda. *Sustainability*, *16*(7), 2878. https://www.mdpi.com/2071-1050/16/7/2878

Zeng, S., Li, T., Wu, S., Gao, W., & Li, G. (2024). Does green technology progress have a significant impact on carbon dioxide emissions? *Energy Economics*, *133*, Article 107524. https://doi.org/10.1016/j.eneco.2024.107524

Zhang, Y., Wang, X., & Feng, N. (2024). The path of green finance to promote the realization of low-carbon economic transformation under the carbon peaking and carbon neutrality goals: Theoretical model and empirical analysis. *International Review of Financial Analysis*, *94*, 103227. https://doi.org/10.1016/j.irfa.2024.103227

Zhao, J. (2024). Impact of green finance on low-carbon transformation: Spatial spillover effects in China. *The North American Journal of Economics and Finance*, *74*, 102202. https://doi.org/10.1016/j.najef.2024.102202

Zhou, Z., Chau, K. Y., Sibghatullah, A., Moslehpour, M., Tien, N. H., & Nizomjon Shukurullaevich, K. (2024). The role of green finance, environmental benefits, fintech development, and natural resource management in advancing sustainability. *Resources Policy*, *92*, Article 105013. https://doi.org/10.1016/j.resourpol.2024.105013

Zuur, A. F., Ieno, E. N., Walker, N., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R*. Springer New York. https://doi.org/10.1007/978-0-387-87458-6

Appendix

Table AT1. Variable, Definition, Calculation Formula, Units, and Data Sources

Note: These data sources refer to these related sources (Ding, 2024; Guo et al., 2024; Hirata, 2024; Liu et al., 2023; Xue & Kan, 2024; Yang et al., 2022).

Variable	Definition	Calculation Formula	Unit
CDEI	Carbon emissions per unit of GDP	CDEI = CE / GDP	Tons CO_2 per 10,000 RMB
CE	Total CO_2 emissions from Scope 1, Scope 2, and Scope 3 for each province	CE = Scope 1 + Scope 2 + Scope 3	10,000 tons CO_2
GDP	Provincial GDP at constant prices	-	Billion RMB
Regions	Administrative region grouping (six regions)	-	Categorical (1–6)
SOL	Time index for study period (2008–2021)	SOL = 1–14 for years 2008–2021	Integer (1–14)