

Article

Does Enhanced Carbon Emission Efficiency Mitigate Urban Climate Risk?

Feiyu Chen ^{1,†} , Xiaoyong Huang ^{1,†} , Zhi Li ^{2,*}, Hanchen Xie ¹ and Yifei Wu ²¹ Research Center of Management Science and Engineering, Jiangxi Normal University, Nanchang 330022, China; cfy99@jxnu.edu.cn (F.C.); 004748@jxnu.edu.cn (X.H.)² College of City Construction, Jiangxi Normal University, Nanchang 330022, China

* Correspondence: gmorning1985@jxnu.edu.cn

† These authors contributed equally to this work.

Abstract

Extreme climate events have emerged as a critical threat to the economic resilience and environmental sustainability of urban systems. As a central pillar of the low-carbon transition, improvements in carbon emission efficiency (CEE) are increasingly recognized as a potential pathway to mitigate the occurrence and intensity of such events. Drawing on a balanced panel dataset of 163 cities from 2006 to 2022, this study integrates an Extreme Gradient Boosting (XGBoost) model augmented with SHAP (Shapley Additive Explanations) analysis and a Geographically and Temporally Weighted Regression (GTWR) framework to examine the nonlinear and spatially heterogeneous effects of CEE on the Climate Physical Risk Index (CPRI). The results reveal a distinct two-stage dynamic pattern, in which CEE initially exacerbates and subsequently mitigates climate risk, indicating a nonlinear transition from short-term intensification to long-term alleviation. This relationship shows clear differences across city levels and climate types. The strongest effects appear in peripheral cities and in areas with extreme rainfall dominance (ERD). Spatial analysis based on GTWR also shows a clear north–south pattern. The effect of CEE in reducing risk becomes stronger from the south to the north. Based on these results, the study suggests different land-use policy strategies for different city types and climate conditions. The results give actionable insights for designing targeted carbon governance policies. These policies aim to deal with the growing challenges caused by extreme climate events under ongoing climate change.

Keywords: extreme climate; climate risks; machine learning; GTWR; carbon emission efficiency; XGBoost–SHAP



Academic Editors: Qiang Yao,
Yan Song, Helin Liu and
Baoqiang Wang

Received: 21 May 2026

Revised: 10 June 2026

Accepted: 13 June 2026

Published: 17 June 2026

Copyright: © 2026 by the authors.
Licensee MDPI, Basel, Switzerland.
This article is an open access article
distributed under the terms and
conditions of the [Creative Commons
Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Against the backdrop of accelerating global warming and the increasing frequency of extreme climate events, greenhouse gas emissions and climate change continue to exert profound and persistent pressures on environmental integrity, economic stability, and social well-being [1]. These pressures have intensified the structural tension between sustained socio-economic advancement and the transition toward low-carbon development. Although China has achieved remarkable economic growth over the past half-century, this progress has come at the cost of resource misallocation and environmental degradation. As early as 2001, the Intergovernmental Panel on Climate Change (IPCC) Third Assessment Report underscored global warming as a critical international political issue, a concern that has since deepened with the continued rise in greenhouse gas emissions and the

escalating occurrence of extreme climate events. In this context, improving carbon emission efficiency (CEE) has become an urgent priority for fulfilling environmental responsibilities and mitigating climate-related risks. China, among the countries most vulnerable to meteorological disasters, has in recent years experienced a pronounced trend of “warming–drying, increasing frequency, and compound extremes” [2]. As a core indicator of low-carbon economic performance, CEE exerts multidimensional effects on social progress, economic development, and emission reduction [3]. The United Nations Sustainable Development Goal 13 (SDG 13) calls for urgent action to fight climate change and its impacts. At the same time, the Chinese government has set the “dual carbon” targets. It aims to reach peak carbon emissions before 2030 and to reach carbon neutrality by 2060 [4]. In this policy and environmental context, improving CEE is an important way to reduce global warming, deal with climate change, and lower climate risks.

A large number of studies have looked at the link between carbon emission efficiency (CEE) and climate risks. These studies mainly focus on how to measure CEE, what affects it, and its environmental effects. Existing research uses data at both the provincial level and the city level [5,6]. Early studies mainly used Data Envelopment Analysis (DEA) to measure CEE. But this method has some limits. It cannot fully capture radial distance functions and may lead to biased results [7]. To solve this problem, recent studies have started to use the Slack-Based Measure (SBM) method, especially the super-efficiency SBM model. This method is now widely used to measure CEE [8]. Beyond measurement, the literature identifies digitalization, information technology, and green credit are key factors that affect CEE [9,10]. From an environmental perspective, regulatory interventions have been shown to stimulate technological progress and thereby enhance CEE [11], while improvements in CEE are widely regarded as instrumental in mitigating global warming and advancing carbon neutrality targets [12]. Parallel research on climate risk mainly looks at how extreme climate events change under global warming and how they affect natural ecosystems [13,14]. Empirical evidence indicates that climate risks in China are getting stronger. The frequency and duration of extreme weather events are both increasing [15]. Carbon emissions are a main source of greenhouse gases, so they are key in climate risk control. Reducing emissions and managing the carbon cycle are widely seen as effective ways. Studies show that lowering the level and growth of emissions can reduce extreme heatwave events [16]. But extreme climate events can also affect emissions. For example, land damage and a decrease in cultivated land can reduce energy demand and total emissions [17,18]. But there are still some gaps. Most studies focus either on the environmental effects of CEE or on how total emissions affect one type of extreme climate event. There is still a lack of clear evidence on how CEE affects complex climate risks. Also, most studies use a linear model. They assume that higher emissions always lead to stronger extreme climate events [19]. In fact, the effects of carbon-related factors are often nonlinear. They may change at different thresholds and depend on the context [8,20]. These effects also differ across climate types, time periods, and regions [14,20]. Accordingly, it is still necessary to study the nonlinear relationship between CEE and combined extreme climate events. It is also important to look at how this relationship changes across space and time.

Overall, it is important to make clear the role of carbon emission efficiency (CEE) in reducing extreme climate risks. This can help meet emission reduction goals under global warming. It can also help deal with the growing challenges that extreme weather brings to the “dual carbon” targets. This study advances the literature in several important respects. First, it develops a rigorous measurement framework by quantifying CEE using a super-efficiency Slack-Based Measure (SBM) model and capturing climate risk through a composite Climate Physical Risk Index (CPRI). Second, it integrates machine learning with causal inference to identify the nonlinear effects of CEE on extreme climate outcomes.

Specifically, an Extreme Gradient Boosting (XGBoost) model within a double machine learning framework is employed to estimate the net mitigation effect of CEE, while Shapley Additive Explanations (SHAP) analysis is used to decompose the relative importance and nonlinear contributions of CEE and other covariates. This approach further enables a comparative assessment across different urban hierarchies and climate regimes. Third, the study employs a Geographically and Temporally Weighted Regression (GTWR) model to uncover the spatiotemporal heterogeneity in the effects of CEE on extreme climate risk, thereby moving beyond conventional aspatial or time-invariant analyses. Finally, drawing on the empirical findings, the study proposes a set of spatially differentiated land-use strategies aimed at enhancing CEE and mitigating extreme climate risks; the technological route is shown in Figure 1. By providing robust quantitative evidence on the nonlinear and heterogeneous impacts of CEE, this study identifies critical threshold effects and differentiated response patterns underlying extreme climate dynamics. The findings offer targeted policy implications for region-specific energy conservation and emission reduction strategies, and generate actionable insights for advancing low-carbon economic development in China under intensifying climate uncertainty.

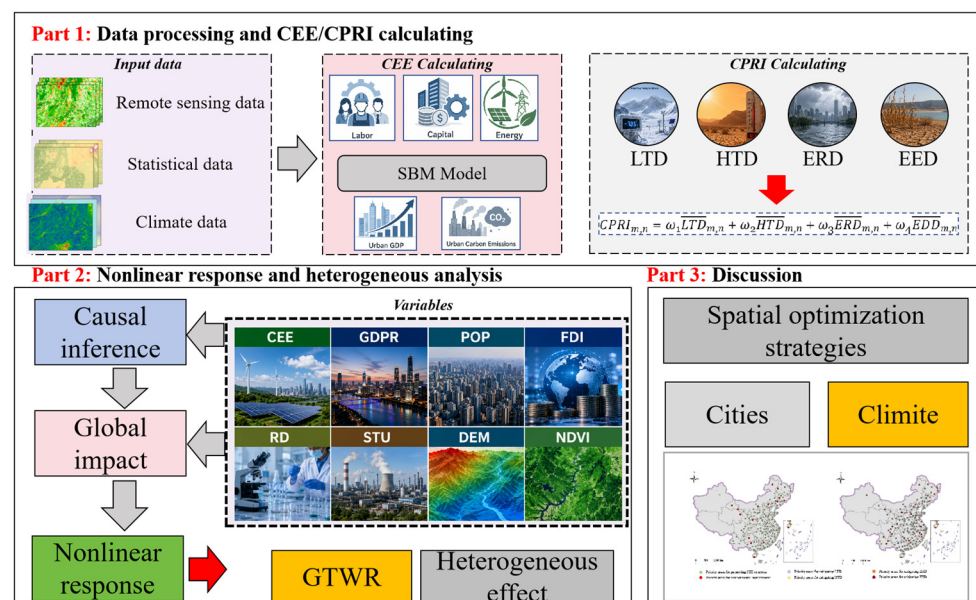


Figure 1. Technological route.

2. Theoretical Framework

Amid intensifying global climate change, the increasing frequency of extreme heat, heavy precipitation, and drought events poses systemic risks to agricultural production, energy systems, and macroeconomic stability. In this context, improving carbon emission efficiency (CEE) is not only essential for achieving carbon neutrality targets, but also represents a critical pathway for mitigating climate risks and enhancing the resilience of socio-economic systems.

From the perspective of neoclassical growth theory, improvements in CEE can be interpreted as a joint outcome of technological progress and more efficient factor allocation. Given fixed inputs of capital and labor, advances in energy efficiency and the adoption of cleaner technologies reduce the carbon intensity of output, thereby enabling a form of relative decoupling between economic growth and emissions. This process not only lowers the marginal environmental externalities associated with production, but also, through price mechanisms and policy constraints, facilitates the reallocation of resources toward low-carbon sectors, fostering a transition toward green growth. As the growth rate of

greenhouse gas emissions slows—or even declines in absolute terms—the accumulation of atmospheric carbon concentrations is moderated, contributing to greater stability in the climate system. Over the long term, this dynamic can help reduce both the frequency and intensity of extreme climate events. Existing studies provide theoretical support for the role of CEE in mitigating climate risks, and the corresponding analytical framework is illustrated in Figure 2.

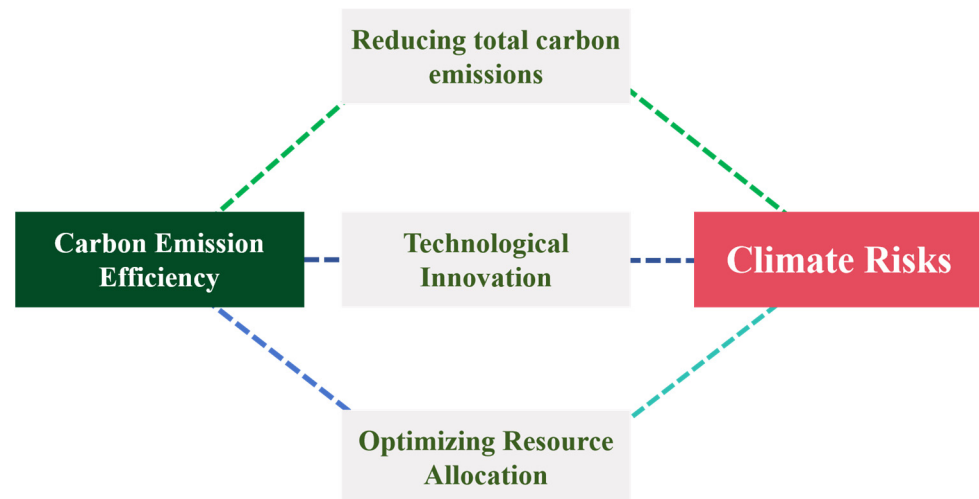


Figure 2. The theoretical framework.

First, the impact of CEE on extreme climate risk should be understood within the broader framework linking economic activities, greenhouse gas accumulation, and climatic responses. Reducing carbon emissions for the same level of economic output can weaken the link between economic growth and emissions. The occurrence of extreme climate events is fundamentally driven by the accumulation of greenhouse gases in the atmosphere, which is closely tied to the carbon intensity of economic production. Improvements in CEE imply that a given level of economic output is achieved with lower carbon emissions, thereby weakening the coupling between economic growth and emissions [21]. While local emission reductions may not immediately alter global climate systems, sustained improvements in CEE across regions contribute cumulatively to mitigating greenhouse gas concentrations, which in turn reduces the probability and intensity of extreme climate events over time. Importantly, the effect of CEE operates through multiple economic channels. Industrial structure plays a central role: a shift from secondary to tertiary industries reduces reliance on energy-intensive production, thereby lowering emission intensity at the source. At the same time, population density influences both emissions and vulnerability. High-density areas tend to generate greater energy demand, but improvements in CEE in such regions can significantly curb aggregate emissions and reduce exposure to climate-related shocks through more efficient infrastructure and resource use.

Second, technological innovation and capital flows constitute key mechanisms linking CEE to climate risk mitigation. R&D investment enhances energy efficiency and accelerates the development and diffusion of low-carbon technologies, thereby reducing emission intensity and fostering adaptive capacity [20]. Similarly, foreign direct investment can introduce advanced production technologies and management practices, contributing to cleaner production processes and improved carbon efficiency [22]. These technological and structural transformations not only reduce emissions but also enhance the resilience of economic systems to climate shocks by promoting diversification and flexibility in energy use and industrial organization.

Third, improving CEE depends on technological innovation. This can directly reduce emissions and also create an “innovation offset” effect. On the one hand, higher carbon efficiency reduces the exposure of economic systems to emission-driven climate change by limiting their contribution to atmospheric warming. On the other hand, structural upgrading and technological progress associated with higher CEE reduce the sensitivity of key sectors—such as agriculture and energy systems—to climate variability [23]. Moreover, innovation-driven efficiency gains strengthen adaptive capacity by enabling more efficient resource allocation, climate-resilient infrastructure, and the adoption of mitigation technologies. Market-based instruments, such as emissions trading systems, further reinforce these effects by incentivizing emission reductions and facilitating the reallocation of resources toward low-carbon sectors.

3. Research Design

3.1. Study Area

The study area includes 163 prefecture-level cities in China (Figure 3). There are clear differences in development among the eastern, central, and western regions. These differences come from industrial structure, energy use, and resource endowments.

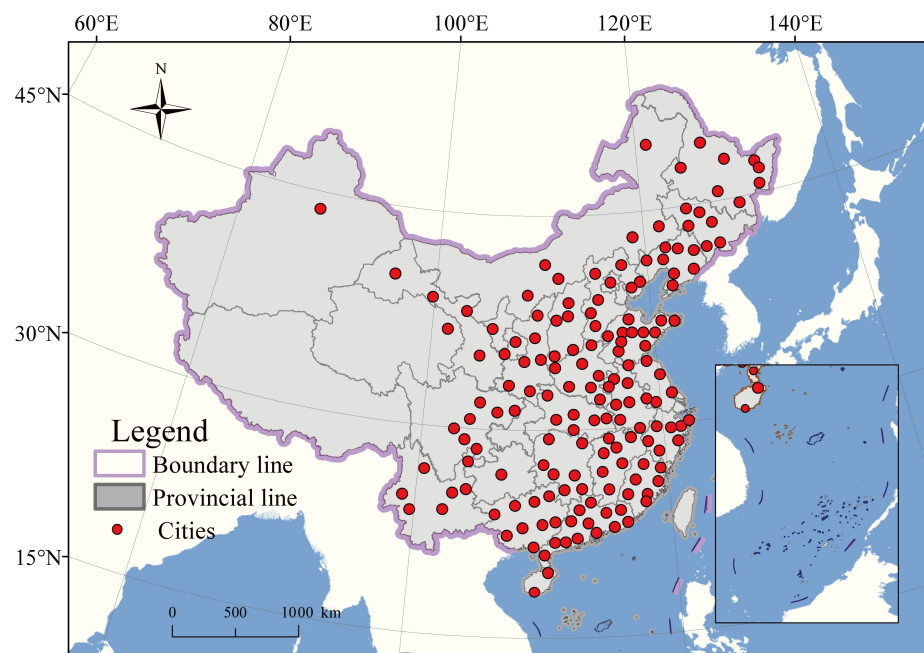


Figure 3. Study area.

These differences lead to clear spatial variation in carbon emissions and in extreme climate events. In this context, it is important to study how extreme climate events interact with carbon emissions across regions. This can help better understand regional climate–carbon links. It can also provide a useful basis for China’s “dual carbon” targets through different and targeted mitigation strategies.

3.2. Methods

As shown in Figure 1, this study uses city-level socioeconomic data and remote sensing data from 2006 to 2022. These data are combined using regional statistical methods. We first build a database of extreme climate events for 163 cities. This includes extreme low temperature (LTD), extreme high temperature (HTD), extreme rainfall (ERD), and extreme drought (EDD). Then, we combine these indicators into a Climate Physical Risk Index (CPRI), which measures climate risk. Next, we use the socioeconomic data to estimate

carbon emission efficiency (CEE) with a super-efficiency Slack-Based Measure (SBM) model. To show the changes in CPRI and CEE over space and time, we use Exploratory Spatial Data Analysis (ESTDA) and Geographic Information Systems (GIS) methods. This helps us study their dynamic spatial patterns in a clear way. Building on this, correlation analysis is conducted as a preliminary step, followed by a causal inference framework based on double machine learning. Specifically, an Extreme Gradient Boosting (XGBoost) model is employed to estimate the causal impact of CEE on climate risk. To further enhance model interpretability, Shapley Additive Explanations (SHAP) analysis is applied to quantify the relative importance and nonlinear contributions of CEE and other explanatory variables in shaping CPRI. Finally, to capture spatiotemporal heterogeneity in the effects of CEE, a Geographically and Temporally Weighted Regression (GTWR) model is implemented. This approach enables a comparative analysis of heterogeneous impacts across different urban hierarchies and climate regimes. Based on the empirical findings, the study further proposes spatially differentiated optimization strategies aimed at mitigating extreme climate risks and supporting the achievement of China's "dual carbon" goals.

3.2.1. Correlation Analysis

We first conduct a correlation analysis to examine the relationships among CEE, CPRI, and other control variables. Specifically, the Pearson correlation coefficient is employed to quantify the strength and direction of linear associations between variables. The coefficient is calculated as follows:

$$R_{ab} = \frac{\sum_{i=0}^n (a_i - \hat{a})(b_i - \hat{b})}{\sqrt{\sum_{i=0}^n (a_i - \hat{a})^2 \sum_{i=0}^n (b_i - \hat{b})^2}} \quad (1)$$

where R_{ab} denotes the Pearson correlation coefficient between variables a and b ; a_i and b_i represent individual observations; and $\hat{a}$ and $\hat{b}$ are the corresponding sample means. This statistic shows the linear relationship between two variables. Its value ranges from -1 to 1 . A negative value means the two variables move in opposite directions. A positive value means they move in the same direction. A larger absolute value means a stronger relationship.

3.2.2. DML

The Double Machine Learning (DML) method is used to estimate the causal effect of one variable on another in the presence of high-dimensional confounders. By combining machine learning with orthogonalization, this approach flexibly captures nonlinear relationships while mitigating overfitting bias. Compared with traditional methods such as difference-in-differences or instrumental variables, DML relies on weaker functional form assumptions and is better suited for high-dimensional settings [24]. The baseline model is specified as follows:

$$CPRI_{it} = \alpha_0 CEE_{it} + f(X_{it}) + \varepsilon_{it} \quad (2)$$

$$E(\varepsilon_{it} | urd_{it}, X_{it}) = 0 \quad (3)$$

In Formulas (2) and (3), i indexes cities and t denotes time; $CPRI_{it}$ represents the dependent variable; CEE_{it} is the treatment variable; α_0 captures the parameter of interest; X_{it} is a vector of control variables; and ε_{it} denotes the stochastic error term.

$$CEE_{it} = g(X_{it}) + \mu_{it} \quad (4)$$

$$E(\mu_{it} | X_{it}) = 0 \quad (5)$$

In Formulas (4) and (5), $g(X_{it})$ denotes the regression function of the treatment variable on the control variables, which is distinct from the outcome function $f(X_{it})$. Following the orthogonalization principle derived from the Frisch–Waugh–Lovell theorem, we partial out the effect of X_{it} by estimating the nuisance functions $g(X_{it})$ and $f(X_{it})$ using machine learning methods. This yields the residuals: $\hat{\mu}_{it} = \text{ur}_{it} - \hat{g}(X_{it})$. These residuals eliminate the influence of high-dimensional controls and allow for consistent estimation of the causal parameter. This step is a partialling-out procedure rather than an instrumental variable approach. Finally, $\hat{\mu}_{it}$ serves as an instrumental variable for estimating the coefficient α_0 .

$$\hat{\alpha}_0 = \left(\frac{1}{n} \sum_{i \in I, t \in T} \hat{\mu}_{it} \text{CEE}_{it} \right)^{-1} \frac{1}{n} \sum_{i \in I, t \in T} \hat{\mu}_{it} [\text{CPRI}_{it} - \hat{f}(X_{it})] \quad (6)$$

To avoid overfitting bias, we implement a five-fold cross-fitting procedure. Specifically, the sample is randomly divided into five subsamples. In each round, four subsamples are used to train the machine learning models for $g(X_{it})$ and $f(X_{it})$, and the remaining subsample is used to generate predictions. This process is repeated five times so that each observation obtains out-of-sample residuals. In estimating the nuisance functions, we employ XGBoost, which allows for flexible modeling of nonlinear relationships. Standard errors are computed using heteroskedasticity-robust estimators to ensure valid statistical inference.

3.2.3. XGboost-Shap

Conventional linear models are often insufficient to capture the complex mitigation effects of CEE on climate risk. To solve this problem, this study uses Extreme Gradient Boosting (XGBoost), which is an improved ensemble learning method based on gradient boosting. It builds and combines many decision trees step by step. In this way, it can capture nonlinear relationships and complex interactions between variables. This helps improve prediction accuracy and identify key driving factors [25]. The mathematical foundation of the XGBoost algorithm is as follows:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (7)$$

The objective function of XGBoost consists of a loss function and a regularization term: the former measures the deviation between predicted and actual values, while the latter controls model complexity to prevent overfitting. The objective function is expressed as follows:

$$\text{Obj} = \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (8)$$

To make the results easier to understand, we also use Shapley Additive Explanations (SHAP). SHAP is based on game theory. It gives each variable a value that shows its contribution to the model result. This method can explain the model at two levels. It can show overall feature importance, and it can also explain each individual prediction. The combination of XGBoost and SHAP provides a useful framework. XGBoost builds a strong prediction model, and SHAP explains how the model works. This helps analyze feature importance, check whether feature ranking matches model behavior, and find nonlinear and different effects in the dataset [26,27]. Compared with studies that only use XGBoost, adding SHAP gives a clearer way to find the drivers of spatial differences in feature effects. This also improves how well the results can be understood in geographic and urban climate studies. We also use SHAP dependence plots to show how CEE affects CPRI. To capture possible nonlinear effects, we fit a LOWESS curve to the SHAP values. Then we find

threshold effects by looking at where the LOWESS curve crosses the zero line. This helps show changes in how CEE affects climate risk.

3.2.4. GTWR

There are clear spatial differences across cities in both CEE and CPRI. This means their relationships may change across space. To deal with this, the Geographically Weighted Regression (GWR) model uses a distance-based weighting method. This allows model coefficients to change by location and improves spatial accuracy. But GWR only works with cross-sectional data and cannot capture changes over time. So, it is not suitable for panel data. To solve this problem, this study uses the Geographically and Temporally Weighted Regression (GTWR) model. This model extends GWR by adding the time dimension to the weighting method. The model is defined as follows:

$$Y_i = \beta_0(\mu_i, v_i, t_i) + \sum_k \beta_k(\mu_i, v_i, t_i)X_{ik} + \varepsilon_i \quad (9)$$

where Y_i denotes the dependent variable; X_{ik} represents the k -th explanatory variable for observation i ; $\beta_k(\mu_i, v_i, t_i)X_{ik}$ is the location- and time-specific coefficient capturing local parameter variation; $\beta_0(\mu_i, v_i, t_i)$ is the intercept term; (μ_i, v_i, t_i) denotes the spatiotemporal coordinates of observation i ; and ε_i is the stochastic error term. By allowing coefficients to change across space and time, the GTWR model provides a flexible way to study spatiotemporal differences. It can also give more accurate results that better reflect different contexts in long panel data.

3.3. Variable Selection

3.3.1. Carbon Emissions Efficiency

Compared with traditional green total factor productivity, carbon emission efficiency (CEE) directly includes carbon emissions as an undesirable output in the evaluation system. When choosing a method, it is important to note that the standard Slack-Based Measure (SBM) model often gives many units an efficiency score of 1. This reduces its ability to distinguish differences and may affect later regression results. To address this limitation, this study adopts a super-efficiency SBM model with undesirable outputs [28], which enables consistent ranking among efficient units and improves estimation accuracy. Within this framework, input variables include labor, capital, and energy consumption; the desirable output is measured by urban GDP; and the undesirable output is proxied by city-level carbon emissions [8]. Detailed variable definitions and data sources are provided in Table 1.

Table 1. Implication and calculation of CEE.

Primary Indicator	Secondary Indicator	Tertiary Indicator
Input Indicators	Labor	Number of employed persons in local administrative units for each year
	Capital	Measured by capital stock. The capital stock is calculated using the perpetual inventory method; a depreciation rate estimated at 9.6% is used in this study [29]; capital denotes capital inflow (in 100 million RMB).
	Energy	Urban direct energy consumption includes natural gas and liquefied petroleum gas, while indirect energy consumption mainly refers to electricity. To ensure consistency, all energy consumption is converted into standard coal equivalent according to the “Comprehensive Energy Consumption Calculation Guidelines.” Conversion coefficients are 1.33 kg tec/m ³ , 1.7143 kg tec/kg, and 0.1229 kg tec/(kWh), respectively.
Expected Output	Urban GDP	Calculated in constant 2006 prices
Unexpected Output	Urban Carbon Emissions	Urban carbon emissions include both direct emissions from energy consumption such as natural gas and liquefied petroleum gas, and indirect emissions from electricity and heat consumption [30].

3.3.2. Extreme Climate Risk

Extreme climate events are defined as rare occurrences that significantly deviate from historical norms and lie in the tails of the probability distribution of climatic variables [14]. Building on existing high-resolution datasets [31] this study constructs a comprehensive measure of climate risk based on four categories of extreme events: extreme low temperature (LTD), defined as daily mean temperature below the 10th percentile of the historical distribution; extreme high temperature (HTD), defined as daily mean temperature above the 90th percentile; extreme rainfall (ERD), defined as daily precipitation exceeding the 95th percentile; and extreme drought (EDD), defined as daily humidity below the 5th percentile. For each meteorological station, the annual number of days corresponding to these four types of extreme events is calculated and subsequently aggregated to the city level using arithmetic averaging, yielding annual city-level indicators of extreme climate exposure. To ensure comparability across indicators with heterogeneous units and scales, all sub-indicators were standardized using a min–max normalization procedure when constructing the Climate Physical Risk Index (CPRI), thereby transforming them onto a unified 0–100 scale. In accordance with the specifications of the original CPRI dataset, each standardized metric was geographically interpolated to the city level and then aggregated using the equal-weight method to generate the comprehensive CPRI [31].

3.3.3. Control Variables

To more accurately isolate the effect of carbon emission efficiency (CEE) on the Climate Physical Risk Index (CPRI), this study includes several control variables. These variables reflect economic development, governance, environmental conditions, and resource endowments. Economic development (GDPR) is measured by the GDP growth rate (%), which shows the level of economic activity. Population density (POP) is measured as the number of people per square kilometer, and it reflects the intensity of human activity and its possible impact on climate, land use, and the economy. Foreign direct investment (FDI) is measured by the actual amount of foreign capital utilized in the current year (in US dollars). Research and development intensity (RD) is measured by internal R&D spending (in ten thousand yuan), and it reflects the level of technological innovation. Natural and environmental factors are also included. The digital elevation model (DEM) is used to show the effect of terrain on climate. The normalized difference vegetation index (NDVI) is used to reflect vegetation cover and environmental conditions. Industrial structure (STU) is measured by the share of the tertiary sector in GDP, and it shows the level of economic upgrading and resource allocation.

3.4. Data Sources and Descriptive Statistics

The dataset integrates geographic, environmental, and socioeconomic information. The CPRI is derived from the established CPRI research database [31], which is constructed using global climate data provided by the National Oceanic and Atmospheric Administration (NOAA). In addition to the CPRI, we report the pre-normalization values of its component indices—extreme low temperature (LTD), extreme high temperature (HTD), extreme rainfall (ERD) and extreme drought (EDD)—to preserve the original data distribution. Digital Elevation Model (DEM) and Normalized Difference Vegetation Index (NDVI) data were obtained from the Resource and Environment Science Data Center, with spatial resolutions of 30 m and 1000 m, respectively. All remote sensing data were processed using ArcGIS 10.2 and projected into the Albers Equal-Area Conic coordinate system to ensure spatial consistency. Socioeconomic data used to compute CEE and other control variables were collected from provincial and municipal statistical yearbooks (2006–2022),

the National Bureau of Statistics of China, and official local statistical databases. Descriptive statistics for all variables are reported in Table 2.

Table 2. Descriptive statistics of main variables.

Variable	Obs.	Mean	Std. Dev.	Min	Max
CPRI	2771	26.898	6.201	0.34	86.53
LTD	2771	19.979	9.196	0	100
HTD	2771	44.415	13.136	0	111.71
ERD	2771	24.459	18.445	0	268.75
EED	2771	18.574	11.447	0	87.07
CEE	2771	0.174	0.131	0.002	1.066
STU	2771	42.454	10.34	11.99	83.87
GDPR	2771	9.697	4.765	−12.3	32.9
POP	2771	391.617	339.298	5	2814
FDI	2771	91.013	203.608	0	1885
RD	2771	60.205	171.953	0.0005	2233.587
NDVI	2771	0.512	0.137	0.066	0.746
DEM	2771	551.637	622.974	1.146	3134.027

4. Results

4.1. Spatio-Temporal Evolution

From a time perspective, carbon emission efficiency (CEE) shows a clear pattern from 2006 to 2022 (Figure 4a,b). It changes from wider spread growth to stronger and more stable performance. In 2006, most CEE values were in the 0–0.35 range. The spatial pattern was scattered, and there were no clear high-efficiency clusters. By 2022, more cities had CEE above 0.35. This shows a shift from local improvement to overall improvement. High-efficiency cities first appeared in some areas and then spread to nearby regions. This may be linked to green technology progress, industrial change, and stronger environmental policy. These effects spread through movement of factors and policy spillovers across regions. From a spatial point of view, CEE shows a clear pattern from coastal areas to inland areas. This pattern becomes more stable over time. The eastern coastal region and parts of the central region gradually form connected high-value areas. This shows stronger spatial clustering. Spatial dynamics (Figure 4c) also show that most cities have positive growth in CEE, especially in the eastern and central regions, where spillover effects are stronger. But some cities show slow growth or decline. This suggests that CEE improvement is still limited by resource conditions, industrial structure, and differences in policy implementation.

In contrast, the spatiotemporal change in the Climate Physical Risk Index (CPRI) shows a more complex spatial pattern. It shows a decline from the northeast to the southwest. The overall level of CPRI increases over time, but the spatial pattern becomes more uneven. On one hand, high-risk areas expand in parts of northern and eastern China. On the other hand, southern and southwestern regions show a relative decline (Figure 4d,e). This pattern shows that climate risk is not only affected by changes in CEE. It is also affected by climate exposure, ecosystem capacity, and governance ability. The dynamic results show that most cities have a moderate increase in CPRI (1–50%). But some cities show negative growth (Figure 4f). This shows that CEE and CPRI do not always change at the same time. This difference suggests that their relationship needs further study, especially in terms of how they are linked and how causality works.

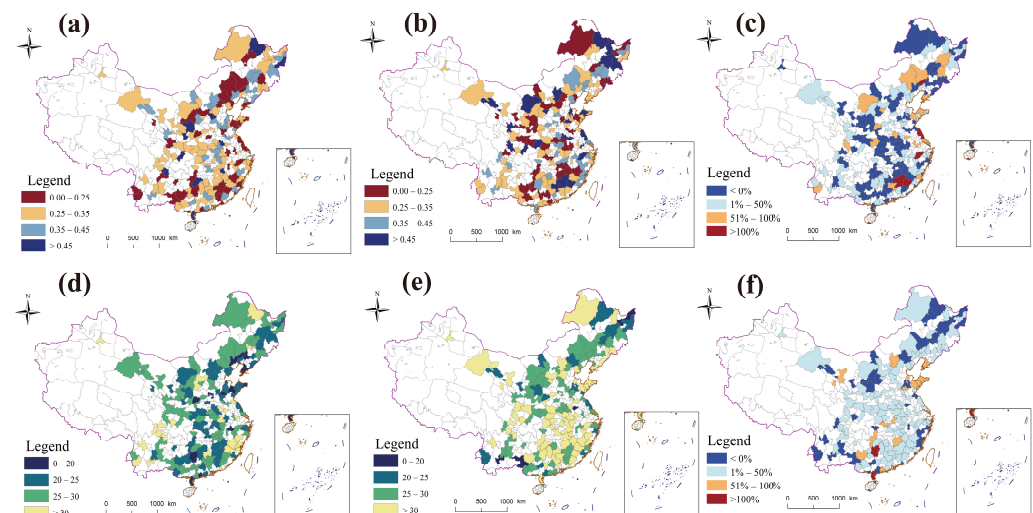


Figure 4. Spatiotemporal distribution and changes in CEE and CPRI. (a) Spatial distribution of CEE in 2006; (b) Spatial distribution of CEE in 2022; (c) Spatial changes of CEE from 2006 to 2022; (d) Spatial distribution of CPRI in 2006; (e) Spatial distribution of CPRI in 2022; (f) Spatial changes of CPRI from 2006 to 2022.

4.2. Quantifying the Mitigating Effect

4.2.1. Correlation Analysis

Prior to empirical modeling, correlation and multicollinearity diagnostics are conducted to ensure the robustness and interpretability of the analysis. The variance inflation factor (VIF) values for all variables are below 10 (see Supplementary Materials), indicating the absence of severe multicollinearity. We then employ the Pearson correlation coefficient to examine pairwise relationships among CEE, CPRI, and control variables (Figure 5), providing a preliminary basis for feature selection and parameter tuning in the subsequent XGBoost model.

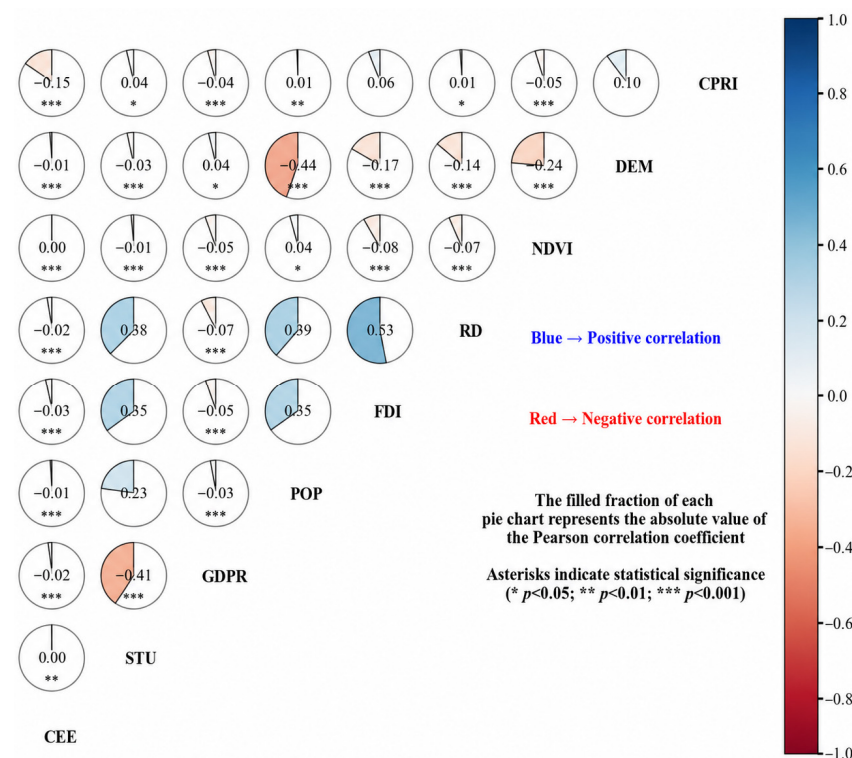


Figure 5. Correlation analysis.

The results show that CEE is significantly negatively correlated with CPRI ($r = -0.15$, $p \leq 0.01$), suggesting that higher carbon efficiency is associated with lower climate risk. Among control variables, NDVI exhibits the strongest negative correlation with CPRI ($r = -0.05$, $p \leq 0.01$). In contrast, population density (POP) and industrial structure (STU) are positively correlated with CPRI ($r = 0.01$, $p \leq 0.05$; $r = 0.04$, $p \leq 0.1$). Overall, the negative link between CEE and CPRI is clear, but the correlation is not very strong. This suggests that the relationship may be more complex and not fully linear. So, it is necessary to use interpretable machine learning methods to better understand the nonlinear patterns behind it.

4.2.2. Causal Inference

To identify the causal link between CEE and CPRI, this study uses a Double Machine Learning (DML) framework. An XGBoost-based DML model is applied. It includes time fixed effects and individual fixed effects to control for unobserved factors and other confounding variables. The dataset is divided into two parts, 80% for training and 20% for testing, with 5-fold cross-validation employed. This helps check the stability and prediction ability of the model. The estimation results are reported in Table 3. The study results demonstrate that CEE has a statistically significant negative impact on CPRI. Furthermore, we extend the analysis to individual components of extreme climate events—including extreme low temperature (LTD), extreme high temperature (HTD), extreme rainfall (ERD) and extreme drought (EDD)—using the same XGBoost-based DML framework. The aforementioned results indicate that higher CEE significantly alleviates all four types of extreme climate events.

Table 3. Causal Inference Results Based on DML.

Variables	(1) CPRI	(2) LTD	(3) HTD	(4) ERD	(5) EDD
CEE	−10.289 ***	−1.129 ***	−5.221 **	−31.008 ***	−5.793 ***
Z Statistic	−8.91	−3.77	−2.78	−7.12	−2.90
Std. Error	1.155	0.299	1.878	4.355	1.997
Control Variables	YES	YES	YES	YES	YES
Machine Learning Model	XGBoost	XGBoost	XGBoost	XGBoost	XGBoost
Time Fixed Effects	YES	YES	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES
Sample Size	2771	2771	2771	2771	2771

Note: ***, **, and * refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

However, the statistical significance of the DML estimates does not, in itself, establish causality. Potential reverse causality between CEE and CPRI, as well as omitted variable bias, may still give rise to endogeneity concerns. To address this, we construct a shift-share instrumental variable based on the interaction between cities' initial industrial structure and the national trajectory of green technological development, and incorporate it into the DML framework. In addition, using the median estimate selected by DML, we implement two-stage least squares (2SLS) regressions as a complementary identification strategy [32].

Specifically, a city's initial industrial structure is proxied by the ratio of tertiary to secondary industry output in 2005, while the national trend in green technological progress is measured by the total number of green patents granted nationwide. The identification strategy rests on two considerations. First, initial industrial structure captures historical dependence on energy-intensive and high-emission sectors, exhibiting strong path dependence and, as a baseline characteristic, is plausibly exogenous to subsequent extreme climate shocks. Second, national green technological progress represents an exogenous macro-level shock, driven primarily by the evolution of the national innovation system and

technological trajectories, and is unlikely to be endogenously determined by climate risk conditions in any single locality.

The interaction term therefore captures cross-regional heterogeneity in exposure to a common technological shock, conditional on pre-existing industrial endowments, and provides an exogenous source of variation in carbon emission efficiency. Under the exclusion restriction—that the instrument is correlated with CEE but does not directly affect regional CPRI—the identification is valid. The corresponding estimation results are reported in Table 4: column (1) presents the DML-based instrumental variable estimates, while columns (2) and (3) report results based on the DML median specification and 2SLS regressions, respectively.

Furthermore, we exploit the low-carbon city policy as a quasi-natural experiment and implement a staggered difference-in-differences (DID) design to identify exogenous shocks to carbon emission efficiency [8], thereby providing an additional check on endogeneity. Given that heterogeneous treatment effects in multi-period DID settings may bias conventional parallel trends tests and spatial-temporal mixed placebo tests [33], we adopt a dynamic specification with event-study-based parallel trend diagnostics. The results are presented in the Supplementary Materials.

Table 4. Endogeneity issues.

Variables	(1) CPRI	(2) CEE	(3) CPRI
IV		0.0170 *** (4.86)	
CEE	−11.467 *** (−3.88)		−1.540 *** (−6.19)
Std. Error	2.966	0.00349	0.250
Control Variables	YES	YES	YES
Machine Learning Model	XGBoost	XGBoost	XGBoost
Time Fixed Effects	YES	YES	YES
Individual Fixed Effects	YES	YES	YES
Sample Size	2771	2771	2771

Note: ***, **, and * refer to statistical significance at the 1%, 5%, and 10% levels; Z-statistic in parentheses.

4.2.3. Global Impact Analysis

To evaluate the relative importance of multiple determinants of the Climate Physical Risk Index (CPRI), we conducted a global impact analysis based on machine learning. After benchmarking alternative models, Extreme Gradient Boosting (XGBoost) was selected as the primary explanatory framework due to its superior predictive accuracy and interpretability. Detailed information on model performance comparisons is provided in Table 5. We combined data from all cities and years as training samples. Similar to DML, a random 80% of the dataset was allocated for model training, while the remaining 20% served as a test set to ensure the model's robustness and generalization capacity. Hyperparameters were optimized through a grid search methodology. The final optimal parameter combination is provided in the Supplementary Materials.

Feature importance is ranked according to the mean absolute Shapley Additive Explanations (SHAP) values (Figure 6a,b). The main findings are as follows. First, relative to other predictors, carbon emission efficiency (CEE) emerges as the most influential factor in mitigating extreme climate risk within the predictive framework. Its mean SHAP value reaches 0.999 (ranked first), accounting for 21.4% of total feature importance, also the highest among all variables. Second, to further explore cross-city heterogeneity [34], we group the aggregated SHAP results by city type (Figure 6c). The results indicate that the effect of CEE is substantially stronger in peripheral cities (mean SHAP value = 0.709) than

in central cities (mean SHAP value = 0.637), highlighting pronounced spatial variation in its predictive contribution. Third, across different types of extreme climate events, the mean SHAP values of CEE for high-temperature days (HTD) and extreme rainfall days (ERD) are 1.121 and 1.334, respectively, whereas the corresponding values for low-temperature days (LTD) and extreme event days (EED) are 0.525 and 0.541. This pattern suggests that CEE exhibits greater explanatory power for HTD and ERD, while its contribution to LTD and EED is comparatively weaker.

Table 5. Comparison Results of Different Models.

Model	Dataset	R2	MSE	RMSE	MAE
Decision Tree	Train	0.804	0.563	0.798	0.520
	Test	0.778	0.858	1.005	0.576
Gradient Boosting	Train	0.852	0.474	0.639	0.436
	Test	0.775	0.770	0.868	0.541
Linear Regression	Train	0.594	1.123	1.064	0.716
	Test	0.464	1.663	1.350	0.770
MLP	Train	0.538	1.281	1.185	0.792
	Test	0.334	2.140	1.492	0.809
Random Forest	Train	0.868	0.492	0.761	0.493
	Test	0.756	0.833	0.928	0.583
XGBoost	Train	0.922	0.333	0.619	0.404
	Test	0.891	0.615	0.815	0.520

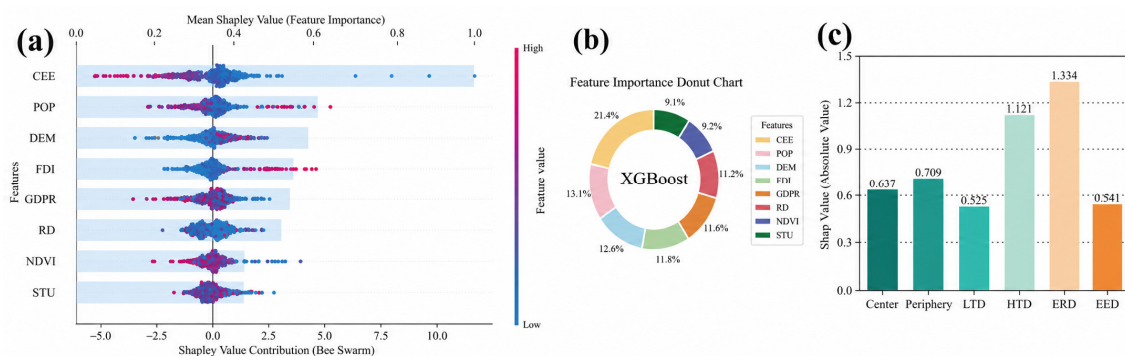


Figure 6. Relative contributions of different factors. (a) Mean Shapely Value; (b) Feature Importance Donut Chart; (c) Shapely Value in Subsamples.

4.2.4. Nonlinear Effects

Figure 7 shows the LOWESS results of the nonlinear relationship between CEE and CPRI. We further examine the relationship between CEE and CPRI, as well as other covariates, using LOWESS smoothing, complemented by instability assessments based on 90% confidence intervals (see Supplementary Materials). The fitted curve suggests a turning point at approximately $CEE \approx 0.18$. However, this value should not be interpreted as a precise causal threshold or policy-relevant cutoff; rather, it represents an approximate point at which the association between the two variables changes direction. Overall, the relationship between CEE and CPRI exhibits a two-stage nonlinear pattern, characterized by an initial intensification followed by mitigation. At relatively low levels of CEE, improvements in efficiency are associated with higher levels of CPRI, indicating a positive association in the early stage. Once CEE surpasses the approximate threshold, the relationship reverses, and further increases in CEE are associated with reductions in CPRI. This pattern suggests that only after reaching a certain level of carbon emission efficiency can its

mitigating effect on extreme climate risk become operative and substantively reflected in the predictive framework.

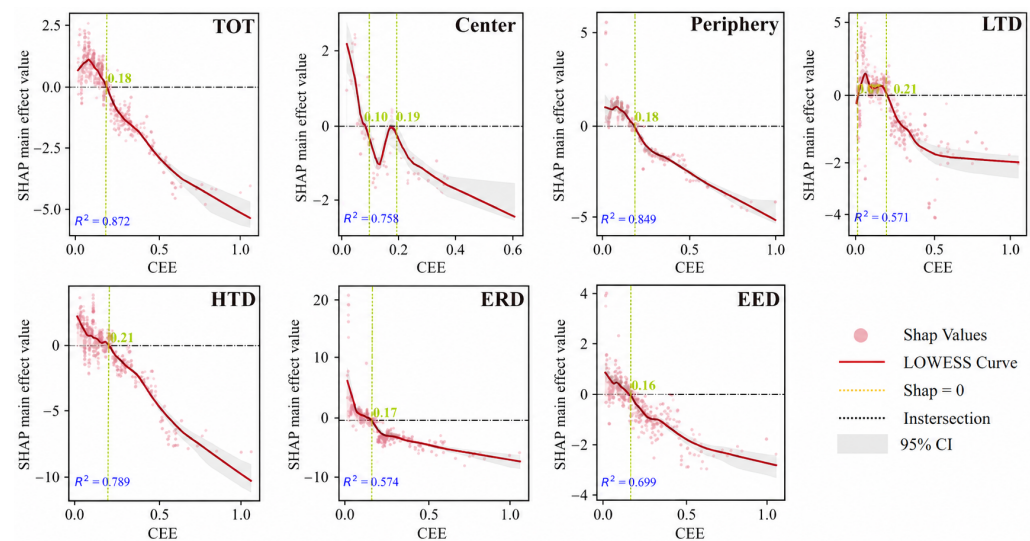


Figure 7. Nonlinear effects.

Subsample analysis reveals pronounced spatial heterogeneity. Central cities exhibit a more complex three-stage nonlinear pattern, characterized by a “mitigation–intensification–re-mitigation” trajectory, with a higher second-stage threshold than that observed in peripheral cities. These results suggest that differences in urban scale and functional structure condition the impact of carbon emission efficiency (CEE) on climate physical risk (CPRI).

Specifically, in central cities, the mitigating effect of CEE follows a more intricate adjustment process, with relatively higher thresholds required to achieve effective risk reduction (0.10 in the first stage and 0.19 in the second stage). By contrast, in peripheral cities, structural characteristics such as simpler urban form and lower levels of economic development are associated with a lower effective threshold (approximately 0.18), indicating that improvements in CEE can translate into risk mitigation at earlier stages. This contrast highlights substantial heterogeneity across city types in both the level and effectiveness of CEE.

Further disaggregation by climate event type reveals distinct differences in response thresholds. The effects of CEE on low-temperature days (LTD) and high-temperature days (HTD) emerge at relatively higher thresholds (around 0.21), whereas its effects on extreme rainfall days (ERD) and extreme drought events (EED) materialize at lower thresholds (approximately 0.16 and 0.17, respectively). This pattern reflects underlying differences in the temporal dynamics of extreme climate events: temperature-related extremes typically evolve over longer horizons, leading to more gradual responses to changes in CEE, whereas precipitation- and drought-related events are more closely tied to short-term fluctuations [35], allowing CEE to exert its influence at earlier stages.

4.3. Spatial–Temporal Heterogeneity Analysis

Given the substantial variation in the effects of carbon emission efficiency (CEE) on the Climate Physical Risk Index (CPRI) across regions and over time, we employ a Geographically and Temporally Weighted Regression (GTWR) model to further investigate these spatiotemporal dynamics. Prior to estimation, global Moran’s I tests are conducted for CEE and CPRI across all years, cities, and functional zones, confirming significant spatial autocorrelation (see Supplementary Materials). We then visualize the spatial distribution of regression coefficients for 2006 and 2022 (Figure 8a,b), and compute annual average

coefficients based on GTWR estimates over 2006–2022 (Figure 8c,d), thereby deriving city-level and year-specific mean spatial effects [25]. The results reveal pronounced spatial heterogeneity in the impact of CEE on CPRI, reflecting systematic variation across both geographic space and time. Detailed GTWR parameter estimates are reported in the Supplementary Materials.

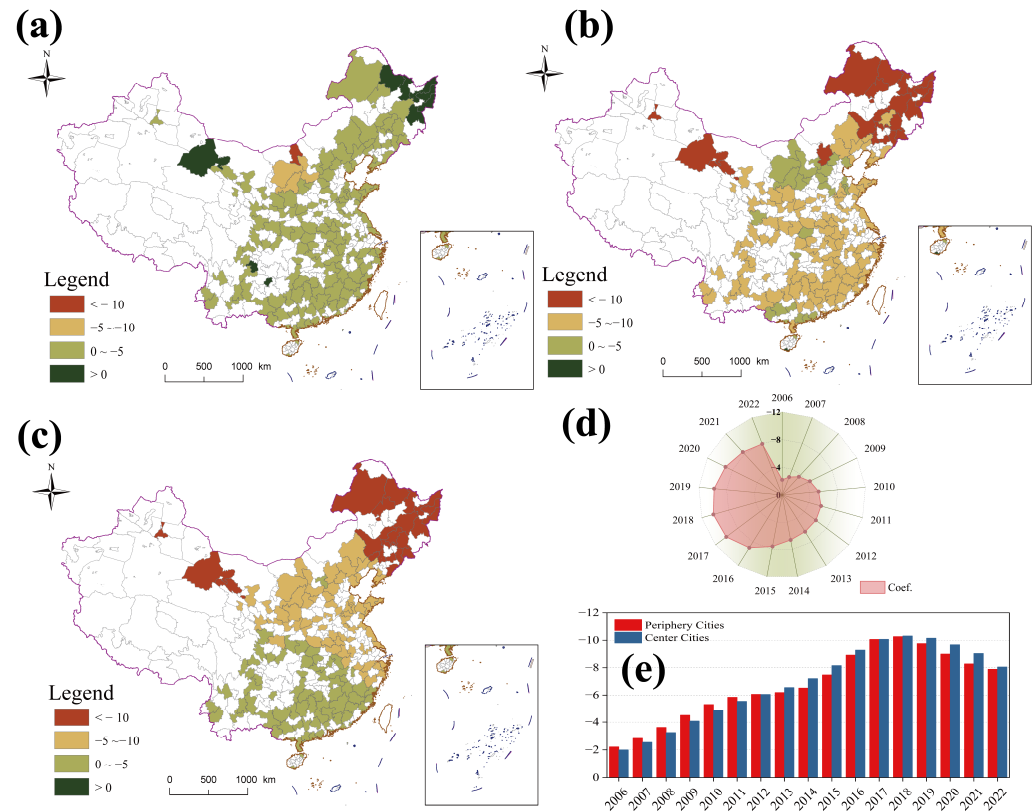


Figure 8. Spatiotemporal heterogeneity of the impact of CEE on CPRI. (a) Spatial distribution of GTWR coefficients in 2006; (b) Spatial distribution of GTWR coefficients in 2022; (c) Spatial average of GTWR coefficients from 2006 to 2022; (d) Annual average of GTWR coefficients from 2006 to 2022; (e) Average across sub-samples of GTWR coefficients from 2006 to 2022.

Three main findings emerge. First, over time, the number of regions exhibiting negative regression coefficients increases, and the absolute magnitude of these coefficients also grows (Figure 9a,b,d), indicating that the mitigating effect of CEE on CPRI becomes progressively stronger. Second, from a spatial perspective, the estimated coefficients are relatively larger in northern regions of the Yangtze River—particularly in northeastern and western areas such as Heilongjiang and Gansu—whereas smaller (though still significantly negative) coefficients are observed in southern regions, especially in southeastern coastal provinces such as Guangdong and Fujian (Figure 9c). Third, from the perspective of city type, the mitigating effect of CEE on extreme climate risk is initially more pronounced in peripheral cities than in central cities. However, over time, the absolute magnitude of the coefficients in central cities surpasses that of peripheral cities, suggesting a stronger long-term mitigation effect in central urban areas (Figure 8e).

To interpret the observed spatial heterogeneity, we propose several plausible mechanisms. Geographic variation may primarily stem from differences in industrial structure between northern and southern regions. As suggested in the theoretical framework, industrial upgrading reduces reliance on energy-intensive sectors, thereby improving carbon emission efficiency (CEE). In particular, northern regions have historically depended on carbon-intensive energy sources and maintain a higher share of heavy industry. By con-

trast, southern regions—especially southeastern coastal provinces such as Guangdong and Fujian—are characterized by service-oriented and export-driven economic structures, along with relatively cleaner energy mixes. As a result, the marginal regulatory effect of CEE on climate physical risk (CPRI) is comparatively weaker in these regions.

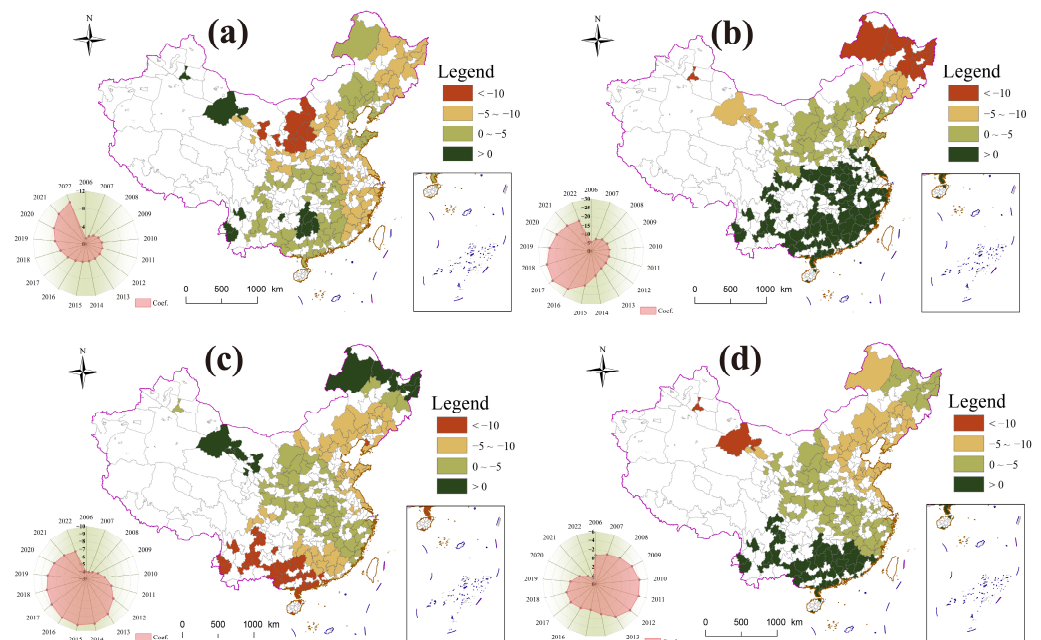


Figure 9. Spatiotemporal heterogeneity of the impact of CEE on EED, ERD, HTD and LTD. (a) Spatial average values of the EED coefficient from 2006 to 2022; (b) Spatial average values of the ERD coefficient from 2006 to 2022; (c) Spatial average values of the HTD coefficient from 2006 to 2022; (d) Spatial average values of the LTD coefficient from 2006 to 2022.

Differences across urban types and over time can be attributed to disparities in infrastructure, governance capacity, and information networks. Central cities typically possess stronger institutional and technological foundations, enabling them to amplify the synergistic effects of policy interventions and technological progress. This cumulative advantage enhances the long-term mitigation impact of CEE. In contrast, peripheral cities tend to face increasing constraints at later stages of development. As inefficiencies are progressively reduced, the marginal elasticity of further improvements in CEE diminishes. At the same time, limited technological absorptive capacity and weaker institutional enforcement hinder the effective translation of efficiency gains into climate governance outcomes, leading to a gradual attenuation of mitigation effects.

Further analysis across different types of extreme climate events (Figure 9) reveals distinct spatiotemporal patterns. The map illustrates the spatial mean effect, while the radar chart demonstrates the temporal mean effect. The mitigating effects of CEE on extreme low temperature (LTD), extreme rainfall (ERD) and extreme drought (EDD) exhibit a clear south-to-north increasing gradient. In contrast, the mitigation effect on extreme high temperature (HTD) follows an opposite pattern, intensifying from north to south. This divergence can be attributed to differences in underlying climate dynamics and human activity intensity. In southern regions—particularly the southeastern coastal areas—high population density and advanced urbanization levels render local thermal environments more sensitive to energy use patterns and emission structures.

5. Discussion

5.1. Ecological, Economic and Urban Land-Use Hierarchy Jointly Shape the Spatial Variation

The spatial analysis shows a clear coastal–inland pattern. Coastal regions have higher carbon emission efficiency (CEE) and lower climate risk (CPRI). This pattern is caused by a mix of ecological, economic, and social factors, not just one factor. Coastal regions have open economies and more diverse industrial structures. They also have advantages in technology, capital, and green development. These conditions help CEE improvements turn into lower climate risk through innovation. In these regions, better digital infrastructure and faster spread of green technology improve energy efficiency and resource use. This reduces carbon intensity and also improves ecosystem regulation ability. As a result, extreme climate risks are reduced at the source. In contrast, inland regions, especially in central and western China, are still dependent on resource-based industries. They also have lower efficiency in factor allocation. So CEE is lower, and its effect on reducing CPRI is weaker. Carbon-intensive industries limit improvements to small and local changes. At the same time, weaker ecological conditions and higher climate sensitivity reduce the ability of CEE improvements to offset climate risks.

From the perspective of urban hierarchy, the interaction among climate change, carbon emissions, and land-use patterns shows clear differences between center cities and peripheral cities. Center cities are usually regional growth centers. They have high population density, service-based industries, and intensive land use. These features support higher CEE through agglomeration effects, technological progress, and more efficient energy use. However, fast urban expansion and the continuous conversion of ecological land into built-up land reduce carbon sink capacity. They also increase urban heat island effects, which raise exposure to extreme climate events. In this context, the link between CEE and CPRI in core cities shows a clear tension. Even if CEE improves, the ability of the ecosystem to buffer climate risk can still weaken due to stronger land-use pressure.

In contrast, peripheral cities usually have lower levels of industrial upgrading, more extensive land use, and stronger dependence on resource-based and carbon-intensive industries. These regions often still have more ecological land, such as forests and farmland. However, they have limited ability to turn these ecological resources into effective climate risk reduction because of weak technology input and weak governance. In addition, extensive land use, especially the expansion of low-efficiency industrial land, increases carbon emission rigidity. This also limits improvements in CEE.

5.2. The Impact of CEE on CPRI Varies Across Spatio-Temporal Factors

Our findings reveal that the mitigating effect of CEE on climate risk follows a characteristic two-stage pattern, shifting from attenuation to reinforcement, with notable heterogeneity across urban and climatic contexts. This evidence suggests that improvements in CEE do not uniformly translate into climate risk mitigation; rather, their effectiveness depends on the dynamic alignment among technological accumulation, institutional capacity, and resource endowments. From a process perspective, the initial stage of CEE improvement typically coincides with phases of rapid economic expansion and rising energy demand. During this period, efficiency gains primarily reflect relative decarbonization—that is, reductions in emissions per unit of output—while total emissions may continue to increase. As a result, the mitigating effect on extreme climate risk remains limited or even weakens. At the same time, the absence of strong complementarities between environmental regulation and green technology diffusion constrains the translation of efficiency gains into effective climate governance outcomes, leading to a diminishing marginal effect.

When CEE passes a key threshold, the pattern changes. Stronger institutions, such as carbon markets, emission limits, and stricter regulation, help turn efficiency gains into

real emission reductions. At the same time, the faster spread of green technology and better energy structure create joint structural and technological effects. In this stage, the marginal effect of CEE becomes stronger again, and it reduces CPRI more clearly. From a spatial point of view, the changes are different across city types. Central cities have stronger innovation ability and better institutional support. They can better turn post-threshold CEE gains into energy system transformation. So they show stronger long-term reduction effects. In contrast, peripheral cities first benefit from a low-base effect. Early improvements in efficiency bring large gains. But over time, industrial path dependence and weak technology absorption limit further progress. This leads to weaker or even stagnant marginal effects.

From the perspective of climate heterogeneity, the effects of CEE also vary across types of extreme climate events. For events more directly driven by greenhouse gas emissions and energy balance—such as extreme high temperature and extreme rainfall—improvements in CEE exert more immediate and pronounced regulatory effects through reductions in carbon intensity and energy structure optimization. Consequently, the recovery of marginal effects is both faster and larger in magnitude. By contrast, for extreme low temperature and drought events, which are more strongly influenced by large-scale climatic systems or resource endowments, the pathways through which CEE operates are more indirect. As a result, their marginal effects are more easily attenuated in the early stage and recover more gradually over time.

5.3. Spatially Differentiated Land-Use Strategies for Climate Mitigation and Carbon Efficiency

Building on the empirical evidence, it is essential to formulate spatially differentiated land-use strategies to enhance the effectiveness with which improvements in CEE translate into climate risk mitigation (Figure 10).

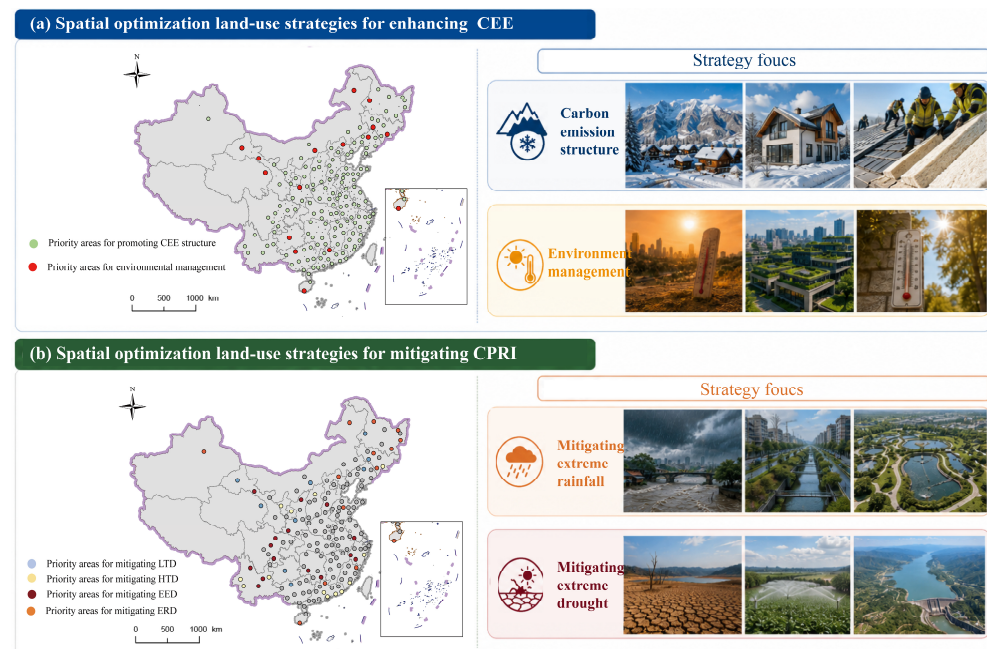


Figure 10. Spatial optimization land-use strategies.

First, for central cities, policy attention may shift from marginal efficiency improvements toward broader spatial and ecological optimization. Given that these cities have already reached relatively high levels of CEE, further gains through conventional efficiency channels appear limited. In this context, optimizing the spatial configuration of land use can serve as a complementary pathway to reinforce carbon efficiency gains. For example,

promoting compact urban development and reducing excessive land expansion may help limit additional carbon emissions associated with urban sprawl.

Second, for peripheral cities, improving CEE may be closely linked to structural transformation processes that are often mediated by land-use patterns. The empirical results suggest that these regions face greater constraints in achieving carbon efficiency improvements, which may reflect their reliance on extensive development modes. In this regard, restructuring land use—such as reducing inefficient industrial land expansion and improving the utilization of existing land resources—can be viewed as a potential policy direction to facilitate low-carbon transition.

Third, considering climate heterogeneity, differentiated adaptation strategies may be necessary to translate carbon efficiency improvements into climate risk mitigation outcomes. The results indicate that the effectiveness of CEE varies across different climate risk contexts. Land-use planning can act as an important policy interface through which such differences are addressed. For instance, in regions exposed to heat-related risks, expanding green infrastructure may help regulate local temperatures, while in areas facing hydrological risks, preserving ecological land may contribute to environmental stability. In colder regions, spatial adjustments in infrastructure and residential layouts may improve energy efficiency.

Finally, from a regional coordination perspective, the results underscore the importance of addressing spatial spillovers and uneven development. Although land-use governance is not explicitly modeled, it may provide an institutional framework for managing cross-regional interactions. Policy tools such as ecological compensation, coordinated spatial planning, and factor mobility mechanisms may help mitigate imbalances between central and peripheral cities. In addition, aligning land-related policies with carbon reduction goals may reduce the risk of emission transfer associated with industrial relocation.

5.4. Limitations

This study examines the causal relationships, explanatory mechanisms, nonlinear interactions, and spatial heterogeneity associated with improvements in carbon emission efficiency (CEE) in mitigating climate risks. Several limitations should be acknowledged. First, the causal interpretation based on the DML framework, even when augmented with instrumental variable (IV) and difference-in-differences (DID) strategies, remains inherently constrained. Although these approaches are employed to strengthen identification, residual endogeneity concerns may persist, implying that the estimated relationships could still reflect conditional statistical associations rather than fully credible causal effects. Second, the construction of the Climate Physical Risk Index (CPRI) using equal weights implicitly assumes homogeneous importance across meteorological stations. In practice, however, substantial heterogeneity exists in geographic conditions and natural endowments across regions. While prior studies suggest that equal weighting introduces limited bias in large-scale, multi-regional analyses, this assumption may be less appropriate for localized contexts. To address this concern, we additionally employ the entropy method to derive data-driven weights for extreme weather indicators, and report the corresponding results as robustness checks in the Supplementary Materials. Third, the interpretation of GTWR results is subject to limitations. Although we provide explanations based on regional differences in industrial structure, energy systems, and institutional capacity, these interpretations rely partly on theoretical reasoning and indirect evidence. Future research should further validate these mechanisms using more direct empirical strategies and richer datasets. Finally, the reliance on XGBoost and GTWR frameworks entails methodological constraints, particularly in capturing complex nonlinear spatial interactions among influencing factors. Future studies could extend the analysis by incorporating a broader sample of cities and employing advanced approaches such as GeoShapley or geographically

weighted random forest models, which may offer improved capacity to characterize spatial heterogeneity and nonlinear dependence structures.

6. Conclusions

This study measures carbon emission efficiency (CEE) and the Climate Physical Risk Index (CPRI) for 163 Chinese cities over the period 2006–2022, and systematically examines their spatiotemporal patterns and interrelationships using Double Machine Learning (DML), XGBoost–SHAP, and Geographically and Temporally Weighted Regression (GTWR). The main findings are as follows. First, CEE exhibits a pronounced coastal–inland gradient, whereas CPRI follows a northeast–southwest declining pattern. Compared with CPRI, the spatial distribution of CEE is more fragmented. Over time, CEE displays heterogeneous dynamics, with both increases and decreases across regions, while CPRI shows a modest overall upward trend accompanied by localized declines. Second, CEE exerts a statistically significant negative effect on CPRI, and this result remains robust after addressing endogeneity concerns. This finding suggests that improvements in carbon emission efficiency contribute to mitigating climate physical risks. Third, the impact of CEE is characterized by clear nonlinearity. Specifically, the relationship follows a two-stage pattern of initial intensification followed by mitigation: when CEE is below the threshold of approximately 0.18, it is positively associated with CPRI, whereas beyond this threshold, it exerts a mitigating effect. Moreover, the threshold, effect size, and direction vary across the distribution of explanatory variables. In peripheral cities and under extreme rainfall conditions (ERD), the mitigating effect emerges at lower thresholds, indicating faster responsiveness. This reflects underlying differences in urban structure and climate sensitivity. Fourth, the relationship between CEE and CPRI exhibits strong spatial heterogeneity. Using the Yangtze River as a natural dividing line, CEE tends to increase climate risk in southern regions while reducing it in northern regions, underscoring the critical role of regional context in shaping the carbon–climate risk nexus. Finally, accounting for heterogeneity across city types and climate conditions, the study proposes differentiated spatial strategies to enhance CEE. Such targeted approaches can more effectively mitigate climate risks under diverse regional conditions and provide empirical support for advancing low-carbon development pathways in China.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15061068/s1>.

Author Contributions: Conceptualization, F.C., H.X., Y.W. and Z.L.; methodology, F.C., X.H., Y.W. and Z.L.; writing—original draft preparation and software, F.C., H.X. and Z.L.; formal analysis and resources, F.C., X.H. and H.X.; validation, investigation, writing—review and editing, and supervision, F.C., X.H., Y.W. and Z.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. 42261046); the National Social Science Fund of China (Grant No. 24FGLB094) and Jiangxi Provincial Department of Education (Grant No. JC21237).

Data Availability Statement: The data is included in the article or Supplementary Materials.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CEE Carbon Emission Efficiency
CPRI Climate Physical Risk Index

References

- Huisingh, D.; Zhang, Z.; Moore, J.C.; Qiao, Q.; Li, Q. Recent Advances in Carbon Emissions Reduction: Policies, Technologies, Monitoring, Assessment and Modeling. *J. Clean. Prod.* **2015**, *103*, 1–12. [\[CrossRef\]](#)
- Liu, Z.; Jiao, L.; Lian, X. Impacts of Increasing Compound Hot-Dry Events on Vegetation under the Warming-Wetting Trend in Northwest China. *Geogr. Sustain.* **2025**, *6*, 100222. [\[CrossRef\]](#)
- Wang, Y.; Han, H. The Impact of China's Carbon Trading Market Launch on Regional Carbon Emission Efficiency. *China Popul.-Resour. Environ.* **2019**, *29*, 50–58. [\[CrossRef\]](#)
- Li, W.; Dong, F.; Ji, Z. Evaluation of Carbon Emission Efficiency and Reduction Potential of 336 Cities in China. *J. Clean. Prod.* **2023**, *428*, 139372. [\[CrossRef\]](#)
- Huang, H.; Wei, Z.; Ge, Q.; Guo, Q. Analysis of Spatial-Temporal Evolution and Influencing Factors of Carbon Emission Efficiency in Chinese Cities. *Front. Environ. Sci.* **2023**, *11*, 1119914. [\[CrossRef\]](#)
- Xie, Z.; Wu, R.; Wang, S. How Technological Progress Affects the Carbon Emission Efficiency? Evidence from National Panel Quantile Regression. *J. Clean. Prod.* **2021**, *307*, 127133. [\[CrossRef\]](#)
- Meng, F.; Su, B.; Thomson, E.; Zhou, D.; Zhou, P. Measuring China's Regional Energy and Carbon Emission Efficiency with DEA Models: A Survey. *Appl. Energy* **2016**, *183*, 1–21. [\[CrossRef\]](#)
- Guo, P.; Liang, D. Does the Low-Carbon Pilot Policy Improve the Efficiency of Urban Carbon Emissions: Quasi-Natural Experimental Research Based on Low-Carbon Pilot Cities. *J. Nat. Resour.* **2022**, *37*, 1876–1892. [\[CrossRef\]](#)
- Han, J.; Jiang, T. Does the Development of the Digital Economy Improve Carbon Emission Efficiency? *Front. Ecol. Evol.* **2022**, *10*, 1031722. [\[CrossRef\]](#)
- Sun, C.; Zeng, Y. Does the Green Credit Policy Affect the Carbon Emissions of Heavily Polluting Enterprises? *Energy Policy* **2023**, *180*, 113679. [\[CrossRef\]](#)
- Pei, Y.; Zhu, Y.; Liu, S.; Wang, X.; Cao, J. Environmental Regulation and Carbon Emission: The Mediation Effect of Technical Efficiency. *J. Clean. Prod.* **2019**, *236*, 117599. [\[CrossRef\]](#)
- Jeltsch-Thömmes, A.; Sun, Q.; Adloff, M.; Joos, F. The Influence of Varying Atmospheric CO₂ on Global Warming Potentials and Carbon Emission Impulse Response Functions. *Environ. Res. Lett.* **2025**, *20*, 064032. [\[CrossRef\]](#)
- Mo, Y.; Zhang, X.; Liu, Z.; Zhang, J.; Hao, F.; Fu, Y. Effects of Climate Extremes on Spring Phenology of Temperate Vegetation in China. *Remote Sens.* **2023**, *15*, 686. [\[CrossRef\]](#)
- Yang, P.; Yang, Y. Impact of Extreme Climate on Carbon Emissions in Planting Industry at the Provincial Level Based on the XGBoost-SHAP Model. *Econ. Geogr.* **2026**, *46*, 215–225. [\[CrossRef\]](#)
- Liu, Z.; Jiao, L.; Lian, X. Changes in Compound Extreme Events and Their Impacts on Cropland Productivity in China, 1985–2019. *Earths Future* **2025**, *13*, e2024EF005038. [\[CrossRef\]](#)
- Park, I.-H.; Yeh, S.-W.; King, A.D. The Pace of Meeting Carbon Emission Targets Alters Regional Climate Risks. *Sci. Adv.* **2026**, *12*, eaec4566. [\[CrossRef\]](#) [\[PubMed\]](#)
- Qian, X.; Qiu, S.; Yang, X. Extreme Weather Exposure and Corporate Carbon Emissions Management: Evidence from Forty Countries. *J. Multinatl. Financ. Manag.* **2024**, *75*, 100872. [\[CrossRef\]](#)
- Minoli, S.; Jägermeyr, J.; Asseng, S.; Urfels, A.; Müller, C. Global Crop Yields Can Be Lifted by Timely Adaptation of Growing Periods to Climate Change. *Nat. Commun.* **2022**, *13*, 7079. [\[CrossRef\]](#) [\[PubMed\]](#)
- Rayer, Q.G.; Andrikopoulos, P. Extreme Weather Attribution: Re-Assessing Company Values Using Carbon Emissions. *J. Appl. Account. Res.* **2026**, *27*, 22–46. [\[CrossRef\]](#)
- Wang, Y.-Q.; Li, J.-Y.; Liu, B.; Wang, F. Spatial Heterogeneity of Carbon Emissions from Construction Projects Based on XGBoost-SHAP. *Huan Jing Ke Xue Huanjing Kexue* **2025**, *46*, 4090–4100. [\[CrossRef\]](#) [\[PubMed\]](#)
- Wang, S.; Wang, Z.; Fang, C. Evolutionary Characteristics and Driving Factors of Carbon Emission Performance at the City Level in China. *Sci. China Earth Sci.* **2022**, *65*, 1292–1307. [\[CrossRef\]](#)
- Borenstein, S. The Private and Public Economics of Renewable Electricity Generation. *J. Econ. Perspect.* **2012**, *26*, 67–92. [\[CrossRef\]](#)
- Shi, R.; Yao, L.; Zhao, M.; Yan, Z. The Role of Climate-Adaptive Technological Innovation in Promoting Agriculture Carbon Efficiency: Impact and Heterogeneity in Economic Development. *Environ. Sci. Pollut. Res.* **2023**, *30*, 126029–126044. [\[CrossRef\]](#) [\[PubMed\]](#)
- Chernozhukov, V.; Denis, C.; Mert, D.; Esther, D.; Christian, H.; Whitney, N.; James, R. Double/Debiased Machine Learning for Treatment and Structural Parameters. *Econom. J.* **2018**, *1*, C1–C68. [\[CrossRef\]](#)
- Li, T.; Liu, Y.; Zheng, Z.; Li, S.; Zheng, X.; Wei, G.; He, B. The Mitigating Effects of Urban Resilience on Surface Urban Heat Islands: Nonlinear Responses, Threshold Effects, and Spatial Heterogeneity. *Sustain. Cities Soc.* **2025**, *131*, 106722. [\[CrossRef\]](#)
- Feng, D.-C.; Wang, W.-J.; Mangalathu, S.; Tacioglu, E. Interpretable XGBoost-SHAP Machine-Learning Model for Shear Strength Prediction of Squat RC Walls. *J. Struct. Eng.* **2021**, *147*, 04021173. [\[CrossRef\]](#)
- Nohara, Y.; Matsumoto, K.; Soejima, H.; Nakashima, N. Explanation of Machine Learning Models Using Shapley Additive Explanation and Application for Real Data in Hospital. *Comput. Methods Programs Biomed.* **2022**, *214*, 106584. [\[CrossRef\]](#) [\[PubMed\]](#)

28. Andersen, P.; Petersen, N.C. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Manag. Sci.* **1993**, *39*, 1261–1264. [[CrossRef](#)]
29. Long, Z.; Herrera, R. Building Original Series of Physical Capital Stocks for China's Economy Methodological Problems, Proposals for Solutions and a New Database. *China Econ. Rev.* **2016**, *40*, 33–53. [[CrossRef](#)]
30. Wu, J.; Wu, Y.; Guo, X.; Cheong, T.S. Convergence of Carbon Dioxide Emissions in Chinese Cities: A Continuous Dynamic Distribution Approach. *Energy Policy* **2016**, *91*, 207–219. [[CrossRef](#)]
31. Guo, K.; Ji, Q.; Zhang, D. A Dataset to Measure Global Climate Physical Risk. *Data Brief* **2024**, *54*, 110502. [[CrossRef](#)] [[PubMed](#)]
32. Jiang, J.; Huang, S. Influence of New Trade Forms on Green Technology Innovation: Based on the Evidence of Cross-Border e-Commerce Comprehensive Pilot Area Policy. *J. Quant. Technol. Econ.* **2024**, *41*, 133–154. [[CrossRef](#)]
33. Chen, Q.; Qi, J.; Yan, G. Placebo Tests for Difference-in-Differences: A Practical Guide. *J. Manag. World* **2025**, *41*, 181–220. [[CrossRef](#)]
34. Li, T.; Li, R.; Liu, Y.; Wei, G.; Li, S.; He, B.-J. Does Enhanced Land Use Efficiency Promote Ecological Resilience in China's Urban Agglomerations? *Environ. Impact Assess. Rev.* **2025**, *115*, 108047. [[CrossRef](#)]
35. Chen, H.; Qi, S.; Tan, X. Decomposition and Prediction of China's Carbon Emission Intensity towards Carbon Neutrality: From Perspectives of National, Regional and Sectoral Level. *Sci. Total Environ.* **2022**, *825*, 153839. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.