Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-13

DOI: *10.15244/pjoes/209836* ONLINE PUBLICATION DATE: 2025-11-12

Original Research

Climate Extremes Increase Air Pollution in China

Diwei Zheng[1], Daxin Dong[2]°*

[1]School of Management, Xiamen University, Xiamen, 361005, China
[2]Institute of Western China Economic Research, Southwestern University of Finance and Economics, Chengdu, 611130, China

Received: 2 May 2025
Accepted: 23 August 2025

Abstract

Existing research has shown that both climate extremes and air pollution have adverse impacts on human health and the economy. It is worth noting that climate extremes and air pollution are not independent of each other. The complex relationship between the two needs more research. In this study, the impacts of climate extremes (extreme low temperature, extreme high temperature, extreme rainfall, and extreme drought) on ambient air pollution are assessed ex post using a multiple regression analysis. Based on data from 223 Chinese cities between 2007 and 2020, our analysis generates three findings. (1) Climate extremes lead to poorer air quality by significantly increasing the concentrations of black carbon (BC), nitrogen dioxide (NO_2), ozone (O_3), organic carbon (OC), particulate matter less than 1 micron in size (PM_1), fine particulate matter ($PM_{2.5}$), particulate matter less than 10 microns in size (PM_{10}), and sulfur dioxide (SO_2). (2) Mechanism analyses suggest that climate extremes increase energy consumption and depress green innovation, which provides explanations for the deterioration of air pollution. (3) Although the effects of different types of climate extremes on air quality vary, in general, it is confirmed that all four types of climate extremes worsen air quality.

Keywords: air pollution, air quality, China, climate extremes, climate risk

Introduction

Research Background

Existing research has shown that both climate extremes and air pollution have severe negative impacts on human health and the economy. There is an urgent need for humanity to take measures to address these problems. It is worth noting that climate extremes and air pollution are not independent of each other. For example, Schnell and Prather [1] observed the co-occurrence of extremes in surface ozone (O_3), fine particulate matter ($PM_{2.5}$), and high temperature over eastern North America during the 1999-2013 period. Marcantonio et al. [2] analyzed data from 176 countries in 2018 and observed a positive correlation between climate risk and toxic pollution. We cannot simply treat the two issues of extreme climate and air pollution in isolation and deal with them separately.

There are at least three possible reasons for the positive correlation between climate extremes and air pollution. (1) Climate extremes and air pollution have some common causes. The occurrence of some extreme climate events and air pollution has common causes that stem from emissions due to human activities. Numerous studies have shown that socioeconomic

*e-mail: dongdaxin@swufe.edu.cn
°ORCID iD: 0000-0002-7161-5112

factors such as economic production activities, population density, urbanization, and industrial structure are among the crucial drivers of air pollution [3, 4]. For example, Hien et al. [5] identified rapid urbanization and urban land expansion as critical factors contributing to atmospheric pollution; Kim et al. [6] demonstrated that population density is a key socioeconomic factor influencing $PM_{2.5}$; Zhao et al. [7] found that vehicle ownership is a significant driver of urban $PM_{2.5}$ levels; Carrión-Flores and Innes [8] and Du et al. [9] emphasized the substantial impact of technological innovation on air pollution concentrations. Moreover, in addition to affecting air quality, these socioeconomic factors interact with environmental systems, triggering a range of extreme conditions [10, 11]. In particular, some types of extreme climate events (e.g., high temperatures, heavy rains, and droughts) are largely due to the accumulation of global greenhouse gases. Economic activities that emit greenhouse gases, especially the burning of fossil fuels and industrial production, often emit air pollutants as well [12, 13]. (2) Climate extremes affect the atmosphere and ecosystem. Climate extremes can alter the state of the atmosphere and ecosystem, influencing the physical and chemical processes through which pollutants are generated and accumulated [14]. Under certain conditions, this may increase the level of air pollution. (3) Climate extremes affect human activities. The occurrence of climate extremes has considerable impacts on human activities that generate emissions [15-17]. For example, in bad weather, humans may increase energy consumption to maintain a suitable living environment. This will increase air pollutant emissions.

In the first case (i.e., climate extremes and air pollution have some common causes), which we have just mentioned earlier, there is only a positive statistical correlation between climate extremes and air pollution. Both occur at the same time. But climate extremes themselves do not affect air pollution. In the second case (i.e., climate extremes affect atmosphere and ecosystem), we need to apply environmental science methods to analyze in detail the complex relationships among climate, atmosphere, and ecosystem conditions, and the generation and accumulation of specific pollutants. These complex relationships cannot be altered by human activities in the short term. In the third case (i.e., climate extremes affect human activities), changes in human activities as well as public policies can make a difference. Therefore, in this study, we focus on the possibility of the third case.

China is a large country with frequent climate disasters and faces great climate risks. For example, according to the China Climate Bulletin 2024, China's nationwide average temperature in 2024 was 10.9 degrees Celsius. This was 1.01 degrees Celsius higher than the average level during 1991-2020 and was the highest in history since 1951. In 2024, there were 42 regional torrential rain events across the country, 4 more than the 1991-2020 average level [18]. China also faces the challenge of air pollution problems. Although the Chinese government and society have made many efforts to reduce air pollution in recent years, many regions are still challenged by air pollution. In 2024, the nationwide average concentration of fine particulate matter ($PM_{2.5}$) was 29.3 μg/m^3 [19]. This value was still much higher than the healthy level recommended by the World Health Organization.

Is there an explicit relationship between climate extremes and air pollution? How do climate extremes occurring in China affect air pollution in this country? These questions are worth studying. By analyzing the influence of climate extremes on air pollution, we can better understand how climate change is shaping the living environment and altering the welfare of humans.

Before formally conducting a rigorous empirical analysis, we observe some visual preliminary evidence. Fig. 1 presents a binned scatter plot for this study's research sample, which covers 223 Chinese cities between 2007 and 2020. The plot is obtained by excluding the city- and year-fixed effects. The Fig. 1 includes eight subfigures, demonstrating the circumstances of eight kinds of pollutants: black carbon (BC), nitrogen dioxide (NO_2), ozone (O_3), organic carbon (OC), particulate matter less than 1 micron in size (PM_1), fine particulate matter ($PM_{2.5}$), particulate matter less than 10 microns in size (PM_{10}), and sulfur dioxide (SO_2), respectively. The vertical axis of the graph shows the average annual concentration of pollution in ambient air; the horizontal axis shows the frequency of climate extremes, which is measured by the climate risk index developed by Guo et al. [20]. This index comprehensively reflects the occurrence of four types of climate extremes: extreme low temperature, extreme high temperature, extreme rainfall, and extreme drought. As displayed in the Fig. 1, climate extremes have a positive correlation with the concentrations of multiple types of air pollutants. Generally speaking, when the degree of climate risk is greater, the level of air pollution is higher. Based on the Fig. 1, it is reasonable to conjecture that climate extremes may increase air pollution.

Research Purpose and Contributions

The research purpose of this study is to analyze whether and to what extent climate extremes affect air pollution using data from a wide range of regions in China. This study contributes to the literature in two aspects. (1) Although it has been previously suggested in the literature that climate extremes affect air pollution, to what extent extreme climate affects air quality has not been adequately analyzed. This study provides evidence from China that climate extremes can indeed lead to air quality degradation. This helps us to gain a deeper understanding of the impact of climate extremes on the environment. (2) This study analyzes a variety of air pollution indicators to provide a more comprehensive picture of air quality changes in China. This provides a new perspective for understanding the air pollution problem in China.

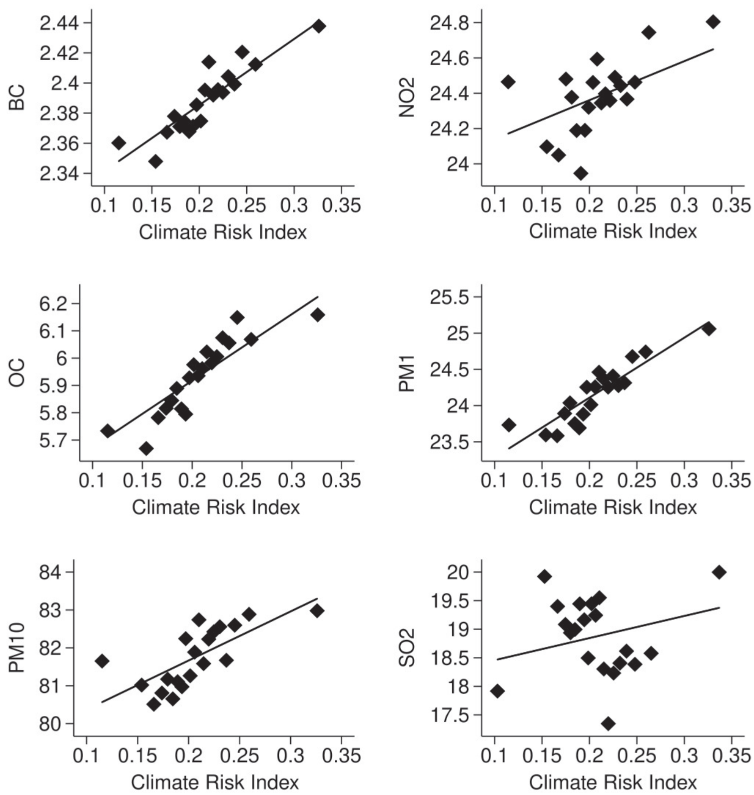

Fig. 1. The positive correlation between climate extremes and air pollution, after excluding the city- and year-fixed effects.
Note: (1) Air pollution is measured by the annual average concentration (μg/m^3) of several pollutants: black carbon (BC), nitrogen dioxide (NO_2), ozone (O_3), organic carbon (OC), particulate matter less than 1 micron in size (PM_1), fine particulate matter ($PM_{2.5}$), particulate matter less than 10 microns in size (PM_{10}), and sulfur dioxide (SO_2); the degree of climate extremes is measured by the climate risk index developed by Guo et al. [20]. (2) The binned scatter plot is obtained by using 20 bins. The graph would be similar if other numbers of bins are used. (3) The data sources are explained in Section "Data source".

Materials and Methods

Regression Model

This study evaluates the impact of climate extremes on air pollution based on the following econometric regression model:

$$AirPollution_{it} = \alpha ClimateRiskIndex_{it} + \beta ControlVariables_{it} + u_i + v_t + \varepsilon_{it} \quad (1)$$

In this Equation, the dependent variable $AirPollution_{it}$ is the level of air pollution in region i in period t. The core explanatory variable $ClimateRiskIndex_{it}$ is an index of climate physical risk, reflecting the frequency of climate extremes. $ControlVariables_{it}$ is a set of meteorological and socioeconomic control variables that may affect air pollution. u_i is the city-fixed effect; v_t is the year-fixed effect; ε_{it} is the residual term.

Variables

Dependent Variable

The dependent variable is $AirPollution_{it}$, the level of ambient air pollution. We examine the annual average concentration (μg/m^3) of several different types of air pollutants: black carbon (BC), nitrogen dioxide (NO_2), ozone (O_3), organic carbon (OC), particulate matter less than 1 micron in size (PM_1), fine particulate matter ($PM_{2.5}$), particulate matter less than 10 microns in size (PM_{10}), and sulfur dioxide (SO_2).

Core Explanatory Variable

The core explanatory variable of interest is $ClimateRiskIndex_{it}$, a composite index of climate physical risk. This variable reflects the frequency of four types of climate extremes, including extreme low temperature (LTD_{it}), extreme high temperature (LHD_{it}), extreme rainfall (ERD_{it}), and extreme drought (EDD_{it}), in region i in year t. This index was constructed by Guo et al. [20] on the basis of historical climatic data. In the section on heterogeneity analysis in this study, we will also separately inspect the impacts of four types of climate extremes. To make it easier to understand the magnitude of the regression coefficients, we rescaled the values of these indices to a range between 0 and 1. Larger index values indicate more frequent occurrences of extreme climate events.

Covariates

The vector $ControlVariables_{it}$ includes the following fourteen meteorological and socioeconomic variables: (1) *Precipitation* is precipitation level (mm); (2) *WindSpeed* is average wind speed (m/s); (3) *Sunlight* is sunlight duration (h); (4) *Temperature* is average temperature (°C); (5) *GDPPerCapita* is GDP per capita (CNY) measured in 2000 constant price level; (6) *Population* is population scale (person); (7) *IndustrialStructure*, is industrial structure measured by the proportion of agricultural value added in GDP; (8) *FinancialDevelopment* is financial development, measured by the ratio of bank credits to GDP; (9) *TradeOpenness* is trade openness, measured by the ratio of international trade volume to GDP; (10) *RoadDensity* is road density calculated by the ratio of road length (km) to land area (km^2); (11) *HighSpeedRail* is a binary dummy variable indicating the connection to the nationwide high-speed railway network; (12) *LowCarbonPolicyIntensity* is an index measuring the intensity of low-carbon policies, scaled to the range between 0 and 1; (13) *InternetDevelopmentPolicy* is a binary dummy variable indicating the operation of the "Broadband China" pilot project; (14) *BigDataDevelopmentPolicy* is a binary dummy variable indicating the operation of the "National Big Data Comprehensive Pilot Zones" project. The data of the variables $Precipitation_{it}$, *WindSpeed*, $Sunlight_{it}$, $GDPPerCapita_{it}$, $Population_{t}$,

Table 1. Descriptive statistics of variables.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
BC	3,053	2.388	1.716	0.050	8.733
NO_2	2,832	24.379	8.883	9.430	54.265
O_3	3,053	86.803	10.250	57.195	122.189
OC	3,053	5.933	3.312	0.213	16.101
PM_1	3,053	24.163	9.034	4.670	59.393
$PM_{2.5}$	3,053	44.201	16.342	12.817	112.078
PM_{10}	3,053	81.748	36.289	21.865	295.404
SO_2	1,727	18.873	11.773	4.952	102.562
ClimateRiskIndex	3,053	0.206	0.058	0.000	1.000
LTD	3,053	0.200	0.093	0.000	1.000
HTD	3,053	0.461	0.136	0.000	1.000
ERD	3,053	0.054	0.053	0.000	1.000
EDD	3,053	0.189	0.121	0.000	1.000
Precipitation	3,053	6.622	0.758	3.290	7.923
WindSpeed	3,053	1.521	0.233	0.765	2.194
Sunlight	3,053	7.617	0.271	6.623	8.129
Temperature	3,053	12.200	6.673	−7.822	25.726
GDPPerCapita	3,053	9.909	0.655	7.842	11.723
Population	3,053	5.754	0.912	2.121	8.074
IndustrialStructure	3,053	0.153	0.094	0.000	0.670
FinancialDevelopment	3,053	0.955	0.608	0.075	5.748
TradeOpenness	3,053	0.205	0.618	0.000	17.176
RoadDensity	3,053	−0.509	0.947	−5.818	0.894
HighSpeedRail	3,053	0.373	0.484	0.000	1.000
LowCarbonPolicyIntensity	3,053	0.330	0.221	0.000	1.000
InternetDevelopmentPolicy	3,053	0.132	0.338	0.000	1.000
BigDataDevelopmentPolicy	3,053	0.082	0.274	0.000	1.000

and $RoadDensity_{it}$ are originally expressed in levels. To mitigate the possible issue of heteroscedasticity, we take logarithms of them and use the log-transformed variables in regression analysis.

Data Source

The data were collected from several sources. (1) The data of BC and OC pollution were from NASA's MERRA-2 M2T1NXAER product. The data of NO_2, O_3, PM_1, $PM_{2.5}$, PM_{10}, and SO_2 pollution were from the GlobalHighAirPollutants (GHAP) dataset [21-24]. The original grid data offered by these data sources were processed to generate the values of annual average concentrations of different pollutants for each Chinese city. (2) The data on climate extremes are provided by Guo et al. [20]. (3) Meteorological data were from the ERA5-Land dataset of the European Union's Copernicus Climate Change Service. (4) The index of low-carbon policy intensity is from Dong et al. [25]. (5) The information about the internet and big data development policies was collected from relevant governmental websites. (6) The other variables, such as GDP per capita and population, were provided by the databases of the Chinese Research Data Services Platform and the EPS China Data.

Research Sample

The research sample was selected on the basis of the data availability of the main variables. In the geographical dimension, the research sample covers 223 Chinese cities. More than 2/3 of Chinese regions have been included in the sample. In the time dimension, the research sample contains 14 years from 2007 to 2020 when we analyze BC, O_3, OC, PM_1, $PM_{2.5}$, and PM_{10}; the sample contains 13 years from 2008 to 2020 when we analyze NO_2; and the sample contains 8 years from 2013 to 2020 when we analyze SO_2. The number of observations ranges from 1727 to 3053, depending on the type of pollutant analyzed. The descriptive statistics of the variables analyzed in this study are reported in Table 1.

Results and Discussion

Main Results

Table 2 reports the results of coefficient estimation for Equation (1). The regression coefficients of $ClimateRiskIndex_{it}$ are all significantly positive when the explained variables are BC, NO_2, O_3, OC, PM_1, $PM_{2.5}$, PM_{10}, and SO_2. This indicates that climate extremes significantly increase air pollution concentration and deteriorate air quality in China. According to the regression results, if the climate risk index increases by one unit, the annual mean concentrations of BC, NO_2, O_3, OC, PM_1, $PM_{2.5}$, PM_{10}, and SO_2 would rise by 0.388, 2.636, 4.681, 2.211, 7.768, 10.89, 13.66, and 6.369 μg/m^3, respectively.

Some other covariates, such as sunlight duration, GDP per capita, industrial structure, and financial development, also have an influence on air quality. Thus, it is reasonable to contain these covariates in the regression equation. Since the covariates are not the focus of this study, we do not discuss their coefficients in detail.

In order to compare the relative magnitude of the influences of climate extremes on different air pollutants, we calculate the standardized regression coefficients. The standardized regression coefficients measure how many standard deviations of change in the explained variables can be caused by a one-standard-deviation change in the explanatory variables. Fig. 2 visually demonstrates the standardized regression coefficients. As can be seen from the Fig. 2, while climate extremes have statistically significant positive effects on all eight types of air pollutants, the relative magnitude of the effects does vary. Extreme climate has the largest effect on PM_1. A one-standard-deviation increase in the extreme climate index causes an increase in PM_1 concentration of about 0.05 standard deviations. The effect of climate extremes on BC was minimal. A one-standard-deviation increase in the extreme climate index causes an increase in BC concentration of about 0.01 standard deviations.

In short, the combined evidence from Table 2 and Fig. 2 demonstrates that climate extremes serve as a critical stressor exacerbating air pollution, while exhibiting pollutant-specific effect magnitudes. The impacts of extreme climate on various air pollutants are qualitatively consistent but quantitatively divergent. On the one hand, all air pollutants show concentration increases under climate extremes; on the other hand, their sensitivity to the same climatic shocks varies substantially across pollutant categories.

Mechanism Analysis

Why do climate extremes increase air pollution? We consider three possible reasons. (1) In order to withstand extreme weather, residents and enterprises may increase their energy consumption. For example, more energy is used to keep warm in cold temperatures. Increased energy consumption can lead to increased pollution emissions. (2) Climate extremes are detrimental to human health and the economy. After extreme climatic events, both human capital and monetary resources that can be used for green innovation are reduced. Reduced green innovation can lead to increased pollution. (3) In extreme climates, governments may shift more attention to responding to extreme climatic events, thereby reducing the focus on air quality protection and the intensity of government environmental regulation. Lower stringency of environmental regulation may lead to greater pollution.

Table 2. Estimated impact of climate extremes on air pollution.

Variables	BC	NO_2	O_3	OC
	(i)	(ii)	(iii)	(iv)
ClimateRiskIndex	0.388***	2.636**	4.681*	2.211***
	[0.050]	*[1.180]*	*[2.734]*	*[0.347]*
Precipitation	−0.0162	−1.007***	−3.106***	−0.243***
	[0.017]	*[0.234]*	*[0.568]*	*[0.081]*
WindSpeed	−0.0511	−1.883**	−6.925***	0.256
	[0.046]	*[0.810]*	*[2.558]*	*[0.207]*
Sunlight	−0.0981**	−1.319**	15.70***	−0.201
	[0.041]	*[0.615]*	*[2.095]*	*[0.252]*
Temperature	−0.00828	−0.126	−0.300	0.298***
	[0.006]	*[0.090]*	*[0.243]*	*[0.055]*
GDPPerCapita	−0.0563**	1.649***	−0.913	−0.00254
	[0.026]	*[0.516]*	*[1.539]*	*[0.147]*
Population	0.0244	−0.622	2.025	−0.0887
	[0.074]	*[1.304]*	*[3.574]*	*[0.302]*
IndustrialStructure	0.562***	3.254	−34.61***	4.288***
	[0.198]	*[2.753]*	*[8.526]*	*[1.399]*
FinancialDevelopment	0.0301**	0.0307	1.390*	0.155*
	[0.015]	*[0.243]*	*[0.819]*	*[0.090]*
TradeOpenness	−0.0042	0.137*	−1.411***	0.0472***
	[0.003]	*[0.076]*	*[0.328]*	*[0.016]*
RoadDensity	0.0432**	0.0398	−1.291	0.309**
	[0.021]	*[0.359]*	*[0.978]*	*[0.140]*
HighSpeedRail	−0.0501***	−0.162	−1.215**	−0.118**
	[0.011]	*[0.186]*	*[0.481]*	*[0.053]*
LowCarbonPolicyIntensity	−0.0797**	−0.627	0.159	−0.377**
	[0.031]	*[0.446]*	*[1.261]*	*[0.151]*
InternetDevelopmentPolicy	−0.0312*	−0.202	1.681**	−0.150**
	[0.017]	*[0.296]*	*[0.822]*	*[0.076]*
BigDataDevelopmentPolicy	−0.0277*	−0.856**	−0.817	−0.229***
	[0.016]	*[0.334]*	*[1.101]*	*[0.066]*
City-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Number of cities	223	223	223	223
Number of observations	3053	2832	3053	3053
Within R^2	0.548	0.566	0.653	0.376

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates.

Variables	PM_1	$PM_{2.5}$	PM_{10}	SO_2
	(v)	(vi)	(vii)	(viii)
ClimateRiskIndex	7.768***	10.89***	13.66***	6.369**
	[1.051]	*[1.913]*	*[4.507]*	*[3.004]*
Precipitation	−1.645***	−3.063***	−4.330***	−4.880***
	[0.248]	*[0.413]*	*[0.864]*	*[0.935]*
WindSpeed	−1.374	−3.447*	−1.384	5.062
	[0.964]	*[1.956]*	*[3.314]*	*[4.446]*
Sunlight	0.116	−0.940	−2.787	−12.09***
	[0.872]	*[1.651]*	*[2.691]*	*[2.757]*
Temperature	−0.202*	0.279	2.464***	1.063***
	[0.103]	*[0.191]*	*[0.374]*	*[0.360]*
GDPPerCapita	0.297	0.771	3.640**	6.964***
	[0.517]	*[0.958]*	*[1.440]*	*[2.486]*
Population	−0.135	−0.212	2.487	−1.951
	[1.334]	*[2.598]*	*[4.587]*	*[7.017]*
IndustrialStructure	11.39***	25.53***	44.64***	51.80***
	[3.431]	*[6.475]*	*[10.242]*	*[12.339]*
FinancialDevelopment	0.0745	−0.386	−0.469	−0.0652
	[0.334]	*[0.627]*	*[0.936]*	*[1.343]*
TradeOpenness	0.0668	0.253***	0.721***	0.507***
	[0.046]	*[0.097]*	*[0.155]*	*[0.155]*
RoadDensity	0.528*	0.776	1.297	−0.716
	[0.312]	*[0.598]*	*[1.088]*	*[4.460]*
HighSpeedRail	−0.571***	−0.454	−0.221	0.509
	[0.205]	*[0.369]*	*[0.571]*	*[0.779]*
LowCarbonPolicyIntensity	−0.808*	−1.547*	−3.239*	−7.761***
	[0.466]	*[0.881]*	*[1.661]*	*[2.864]*
InternetDevelopmentPolicy	−0.841**	−1.338*	−2.142**	−1.711
	[0.359]	*[0.688]*	*[1.051]*	*[1.106]*
BigDataDevelopmentPolicy	−1.004**	−1.855*	−2.986**	−4.056***
	[0.465]	*[0.944]*	*[1.471]*	*[1.421]*
City-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Number of cities	223	223	223	222
Number of observations	3053	3053	3053	1727
Within R^2	0.840	0.833	0.814	0.66

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates.

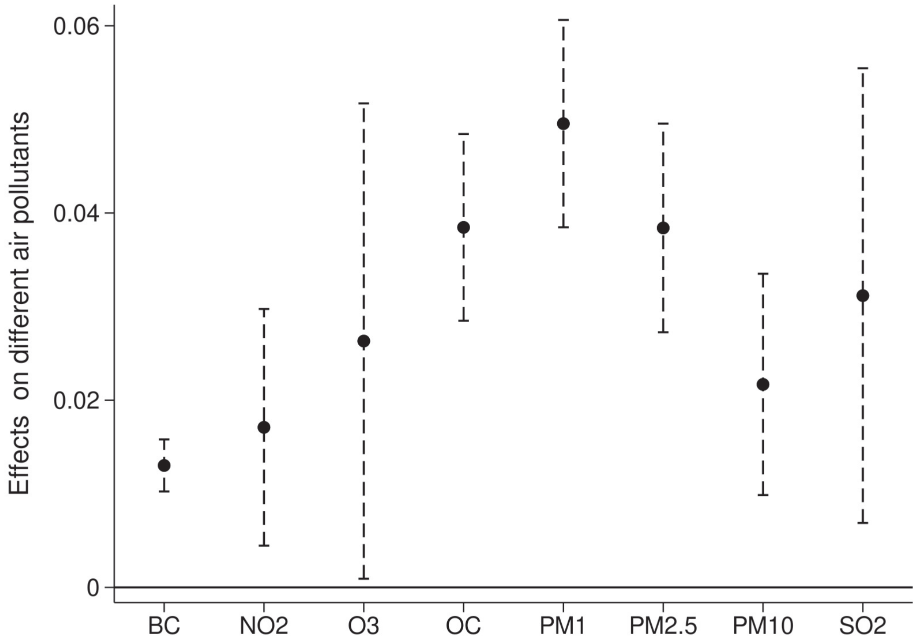

Fig. 2. The standardized regression coefficients.
Note: Solid dots show point estimates of the standardized regression coefficients. Dashed lines demonstrate the corresponding 90% confidence intervals.

We examine each of these three possible mechanisms separately. First, we analyze the effect of climate extremes on energy consumption. Data on energy consumption are provided by Yang et al. [26]. We replace the dependent variable in Equation (1) with the logarithmic value of energy consumption. The regression coefficient is reported in Column (i) of Table 3. The coefficient of $ClimateRiskIndex_{it}$ is significantly positive. This indicates that climate extremes do significantly increase energy consumption.

Second, we analyze green innovation. We measure the degree of green innovation in a region by adding one to the number of green invention patents and taking the logarithm. The data on green patents were from the Chinese Research Data Services Platform. The result of the regression with green innovation as the explanatory variable is shown in Column (ii) of Table 3. The coefficient of $ClimateRiskIndex_{it}$ is significantly negative, indicating that climate extremes reduce green innovation.

Third, we analyze environmental regulation. We measure the stringency of environmental regulation by the proportion of environment-related words mentioned in local governments' annual work reports to the total number of words in the reports. The government work reports were published on government websites. We use environmental regulation as the explained variable, and the regression coefficient is displayed in Column (iii) of Table 3. The coefficient of $ClimateRiskIndex_{it}$ is statistically nonsignificant. We do not find that environmental regulation is significantly affected by climate extremes.

We have just measured environmental regulation stringency using environment-related keyword frequency in government reports. However, we acknowledge that this approach may not fully capture the actual enforcement intensity in policy implementation. For instance, some regions might emphasize environmental rhetoric in official documents without actual strict enforcement, while others may implement stringent policies without abundant keyword mentions. This measurement limitation possibly attenuates the estimated effect, which may partially explain the lack of statistical significance in the regression result. Therefore, we additionally consider three alternative environmental regulation indicators: the removal rate of industrial SO_2, the removal rate of industrial dust, and the utilization rate of industrial solid waste. The removal rate of industrial SO_2 is defined as the ratio of SO_2 captured and removed by pollution control equipment to the total SO_2 generated during industrial production processes. The removal rate of industrial dust is the proportion of dust collected and removed by emission control devices relative to total dust generated in industrial production. The utilization rate of industrial solid waste is calculated as the ratio of comprehensively utilized solid waste to the sum of current-year generation and prior-year stockpiles. Higher values of these indicators reflect stronger local commitment to environmental protection and greater efforts in pollution abatement, indicating more stringent environmental regulation. We employ these three metrics as dependent variables to assess the impact of climate extremes on environmental regulation. The results show statistically

Table 3. Results of mechanism analysis.

Variables	Energy consumption	Green innovation	Environmental regulation
	(i)	(ii)	(iii)
ClimateRiskIndex	0.433***	−0.901***	0.032
	[0.078]	*[0.208]*	*[0.044]*
Control variables	Yes	Yes	Yes
City-fixed effects	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes
Number of cities	214	223	223
Number of observations	2955	3053	3053
Within R^2	0.745	0.772	0.127

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates. The coefficients of control variables are not reported to save space.

nonsignificant coefficients for $ClimateRiskIndex_{it}$ (coefficients not reported here to conserve space), suggesting no significant impact of climate extremes on environmental regulation.

In short, we find that climate extremes increase energy consumption and reduce green innovation. This provides an explanation for the phenomenon that climate extremes increase air pollution.

Heterogeneity Analysis

In the previous analysis, the explanatory variable we used was $ClimateRiskIndex_{it}$. This index combines information on extreme low temperature, extreme high temperature, extreme rainfall, and extreme drought. The value of this index is the average of four sub-indices: LTD_{it}, HTD_{it}, ERD_{it}, and EDD_{it}. The estimated coefficient of $ClimateRiskIndex_{it}$ reflects the average effect of the four types of climate extremes on air pollution. Now, we further explore whether there are some heterogeneities in the effects of the four kinds of climate extremes on air pollution. We replace $ClimateRiskIndex_{it}$ in Equation (1) with four sub-indices to construct the following regression model:

$$AirPollution_{it} = \alpha_1 LTD_{it} + \alpha_2 HTD_{it} + \alpha_3 ERD_{it} + \alpha_4 EDD_{it} + \beta ControlVariables_{it} + u_i + v_t + \varepsilon_{it} \quad (2)$$

where LTD_{it} represents extreme low temperature; HTD_{it} represents extreme high temperature; ERD_{it} refers to extreme rainfall; and EDD_{it} refers to extreme drought.

The coefficient estimates for Equation (2) are reported in Table 4. As the table shows, the effects of different types of climate extremes on air pollution do differ. For example, extreme low temperature, extreme rainfall, and extreme drought have significantly positive effects on most air pollutants; however, extreme high temperature does not have significant effects on any other types of air pollutants except that it increases O_3. It is interesting to note that while extreme rainfall significantly increases SO_2, extreme low temperature and extreme drought have significantly negative effects on SO_2.

The heterogeneities we observe may be due to a variety of complex reasons that are possibly related to factors such as meteorological conditions, economic structure, and the way humans cope with climate extremes in each region. For instance, we take the impacts of four types of climate extremes on SO_2 concentrations as an example to discuss several plausible explanations. (1) Extreme low temperature shows a negative correlation with SO_2 concentrations. This may occur because low temperature is often accompanied by thermal inversions and high-pressure systems, which suppress the dispersion of SO_2 pollutants. (2) Extreme drought reduces SO_2 concentrations, likely because drought leads to soil cracking and increased dust emissions. Airborne SO_2 reacts chemically with the surface of dust particles, promoting its conversion to sulfate aerosols, which then rapidly settle out of the atmosphere, resulting in an observed decline in SO_2 concentrations. (3) Extreme heat has no statistically significant effect on SO_2 levels. This could be attributed to offsetting mechanisms: on the one hand, high temperature may increase electricity demand, raising SO_2 emissions from thermal power plants; on the other hand, heat typically enhances strong convection and vertical dispersion in the atmosphere, diluting SO_2, while accelerated photochemical reactions promote its conversion into other chemical species. These opposing effects balance out, leading to a statistically nonsignificant net impact. (4) Extreme rainfall increases SO_2 concentrations, possibly due to: leaching of sulfur compounds from the ground, re-releasing them as SO_2; overflow events from wastewater treatment plants or industrial facilities during heavy rain, discharging sulfur-containing pollutants; post-disaster economic recovery after floods, which may stimulate industrial

Table 4. Heterogeneity across different types of climate extremes.

Variables	BC	NO_2	O_3	OC
	(i)	(ii)	(iii)	(iv)
LTD	0.175***	3.080***	3.307	1.139***
	[0.047]	*[0.825]*	*[2.396]*	*[0.343]*
HTD	−0.0113	−0.355	3.970***	0.238
	[0.027]	*[0.493]*	*[1.375]*	*[0.172]*
ERD	0.323***	1.170	0.713	1.259***
	[0.051]	*[1.207]*	*[2.509]*	*[0.303]*
EDD	0.176***	2.354***	0.696	1.389***
	[0.031]	*[0.566]*	*[1.659]*	*[0.207]*
Control variables	Yes	Yes	Yes	Yes
City-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Number of cities	223	223	223	223
Number of observations	3053	2832	3053	3053
Within R^2	0.553	0.572	0.655	0.387

Variables	PM_1	$PM_{2.5}$	PM_{10}	SO_2
	(v)	(vi)	(vii)	(viii)
LTD	3.942***	5.756***	8.230***	−9.650***
	[0.947]	*[1.941]*	*[3.161]*	*[3.171]*
HTD	0.246	0.571	1.250	0.762
	[0.537]	*[1.069]*	*[1.779]*	*[1.396]*
ERD	6.681***	8.595***	8.605	11.51***
	[1.123]	*[1.900]*	*[5.316]*	*[2.444]*
EDD	2.378***	4.071***	7.170***	−6.466***
	[0.549]	*[1.062]*	*[1.941]*	*[2.348]*
Control variables	Yes	Yes	Yes	Yes
City-fixed effects	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes
Number of cities	223	223	223	222
Number of observations	3053	3053	3053	1727
Within R^2	0.841	0.834	0.815	0.666

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates. The coefficients of control variables are not reported to save space.

activities and elevate SO_2 emissions. The aggregate of these effects may outweigh the wet deposition removal of pollutants by rainfall, resulting in a net increase in SO_2 levels.

It is not easy to specifically analyze all the possible causes of heterogeneities reported in Table 4. To do this, more detailed data and more sophisticated methods are needed. This is beyond the scope of this study. Therefore, we leave this important but difficult task for future research.

For the different types of climate extremes, although we observe some heterogeneities, we find that all four types of climate extremes significantly increase the concentration of at least one kind of air pollutant.

This finding supports the core viewpoint of this study: climate extremes worsen air quality.

Discussion

As reported in this study, the occurrence of climate extremes exacerbates air pollution. This phenomenon takes a heavy toll on public health and economic development. Effective measures should be taken to address the serious environmental challenges posed by climate change.

First, the government should strengthen the early warning and emergency response mechanisms for extreme climate. As reported by the China Meteorological Administration [18], in recent years, the frequency of climate-related disasters such as extreme heatwaves, torrential rains, and floods has been increasing in China. These extreme climate events not only pose direct threats to public safety but also significantly exacerbate multiple pollution indicators such as NO_2, O_3, and $PM_{2.5}$ (see Table 2), thereby indirectly endangering long-term public health. Therefore, given the compounded threats extreme climate events pose to both public health and environmental quality, there is a need to integrate data from multiple sectors, including meteorology, urban environmental management, and natural ecology protection, to improve the accuracy and timeliness of predictions of extreme climatic events [27]. For different types of extreme climatic events, differentiated emergency response plans and public health strategies should be formulated, and the responsibilities and action plans of each department should be clarified to enhance the efficiency of emergency response. It is also necessary to carry out publicity and education on extreme weather risks, popularize knowledge on disaster prevention and mitigation, and improve public awareness of risks and the ability of self-rescue [28, 29].

Second, China needs to actively adjust its energy structure and promote green innovation. Our mechanism analysis (see Table 3) shows that climate extremes aggravate air pollution through two main channels: increasing energy consumption and suppressing green innovation. Therefore, China should vigorously promote the transition to clean energy and enhance incentive mechanisms for green innovation and environmental research. Although China has made great efforts in transitioning to clean energy, the proportion of clean energy consumption in its total energy mix remains relatively low at present [30]. Clean energy substitution should be accelerated, and the production capacity of high-energy-consuming and high-emission industries should be controlled to reduce greenhouse gas and pollutant emissions. Green innovation should be strongly encouraged. Fiscal, financial, and regulatory instruments can motivate enterprises to phase out old, inefficient, and highly polluting equipment and technologies and to adopt greener and more environmentally friendly production methods [31, 32].

Third, vulnerable areas susceptible to extreme climate impacts have to continuously strengthen ecosystem protection and restoration and enhance ecosystem resilience. Important ecosystem protection and restoration projects that have been implemented previously, such as the Three-North Shelterbelt Forest Program and the Grain for Green Program, need to be maintained [33, 34]. Nature-based solutions such as afforestation, returning farmland to forests and grasslands, and wetland restoration need to be adopted according to local conditions. These actions will mitigate climate change and environmental pollution, and increase the resilience of the ecosystem and society to climate extremes. Furthermore, the heterogeneity analysis results of this study (see Table 4) indicate differential impacts of distinct extreme climate types on various pollutants. Consequently, beyond universal solutions like afforestation, local governments should also formulate targeted governance strategies based on regional climate characteristics and the dominant types of pollutants likely to be triggered. For instance, in areas where high temperatures frequently occur in summer, efforts should be made to strengthen the control of volatile organic compounds (VOCs) emissions to mitigate rising O_3 concentrations.

Last but not least, effectively mitigating extreme climate events requires the implementation of robust climate policies and an emphasis on their roles. However, if governments fail to ensure transparency in information disclosure or frequently alter policies during implementation, public confidence in climate policies may erode, leading to climate policy uncertainty (CPU). Policymakers should not overlook the potential adverse effects of CPU, as it can influence the economic behaviors of firms and the public, thereby affecting emissions and harming the environment. For instance, Attílio [35] and Niu et al. [36] examined samples from multiple economies and found that CPU significantly suppresses green innovation. Yang et al. [37], based on data from 45 countries, demonstrated that when CPU exceeds a certain threshold, the positive effect of environmental taxes on renewable energy development weakens, impeding energy transition. This finding confirms that CPU may interfere with the effectiveness of environmental policies, ultimately harming the environment. Furthermore, utilizing micro-level data from China's listed companies, Wang et al. [38] provided evidence that CPU negatively affects corporate adoption of low-carbon technologies, consequently undermining their carbon emission performance. Therefore, governments should take actions to reduce CPU in order to stabilize corporate expectations, enhance public confidence, and improve the effectiveness of climate policies and environmental governance. Specifically, policymakers can take the following steps. (1) Enhance climate policy transparency and forward-looking planning – clearly define policy objectives, implementation pathways, and technological roadmaps through long-term strategies to reduce arbitrary changes. (2) Establish a stable climate policy evaluation and feedback mechanism – regularly release assessment reports and address concerns from the public and businesses to strengthen policy credibility. (3) Strengthen communication and consultation with stakeholders – encourage public and corporate participation in policymaking through hearings and public consultations to reduce information asymmetry. (4) Embed stable green incentives in fiscal and financial systems – such as mid-to-long-term green credit incentives – to provide institutional stability for corporate green transition. Through these institutional measures, governments can effectively mitigate the disruptive effects of potential CPU, thereby laying a more solid foundation for achieving climate goals and improving environmental quality.

Conclusions

In this study, we utilize data for 223 Chinese cities from 2007 to 2020 to analyze the impacts of climate extremes on air quality. The regression estimation results show that climate extremes significantly increase the concentrations of BC, NO_2, O_3, OC, PM_1, $PM_{2.5}$, PM_{10}, and SO_2. It is found that climate extremes significantly impair air quality in China. Further analysis reveals that extreme climate increases energy consumption and depresses green innovation, which provides explanations for the deterioration of air pollution. Although there are differences in the effects of the four types of climate extremes (i.e., extreme high temperature, extreme low temperature, extreme rainfall, and drought) on different kinds of air pollutants, in general, all four types of climate extremes impair air quality. The findings in this study underscore the imperative for concrete actions to mitigate these emerging environmental challenges.

Acknowledgements

The authors declare that no funds were received for this research.

Conflict of Interest

The authors declare no conflict of interest.

References

1. SCHNELL J.L., PRATHER M.J. Co-occurrence of extremes in surface ozone, particulate matter, and temperature over eastern North America. Proceedings of the National Academy of Sciences of the United States of America. **114** (11), 2854, **2017**.
2. MARCANTONIO R., JAVELINE D., FIELD S., FUENTES A. Global distribution and coincidence of pollution, climate impacts, and health risk in the Anthropocene. PLoS One. **16** (7), e0254060, **2021**.
3. BORCK R., SCHRAUTH P. Population density and urban air quality. Regional Science and Urban Economics. **86**, 103596, **2021**.
4. HOU Y., WANG Q., TAN T. Evaluating drivers of $PM_{2.5}$ air pollution at urban scales using interpretable machine learning. Waste Management. **192**, 114, **2025**.
5. HIEN P.D., MEN N.T., TAN P.M., HANGARTNER M. Impact of urban expansion on the air pollution landscape: A case study of Hanoi, Vietnam. Science of the Total Environment. **702**, 134635, **2020**.
6. KIM M.J., CHANG Y.S., KIM S.M. Impact of income, density, and population size on PM2.5 pollutions: A scaling analysis of 254 large cities in six developed countries. International Journal of Environmental Research and Public Health. **18** (17), 9019, **2021**.
7. ZHAO H., LIU Y., GU T., ZHENG H., WANG Z., YANG D. Identifying spatiotemporal heterogeneity of $PM_{2.5}$ concentrations and the key influencing factors in the middle and lower reaches of the Yellow River. Remote Sensing. **14** (11), 2643, **2022**.
8. CARRIÓN-FLORES C.E., INNES R. Environmental innovation and environmental performance. Journal of Environmental Economics and Management. **59** (1), 27, **2010**.
9. DU S., HE C., ZHANG L., ZHAO Y., CHU L., NI J. Policy implications for synergistic management of $PM_{2.5}$ and O_3 pollution from a pattern-process-sustainability perspective in China. Science of the Total Environment. **916**, 170210, **2024**.
10. BALCH J.K., IGLESIAS V., BRASWELL A.E., ROSSI M.W., JOSEPH M.B., MAHOOD A.L., SHRUM T.R., WHITE C.T., SCHOLL V.M., MCGUIRE B., KARBAN C., BUCKLAND M., TRAVIS W.R. Social-environmental extremes: Rethinking extraordinary events as outcomes of interacting biophysical and social systems. Earth's Future. **8** (7), e2019EF001319, **2020**.
11. XIE Y., ZHOU Z., SUN Q., ZHAO M., PU J., LI Q., SUN Y., DAI H., LI T. Social-economic transitions and vulnerability to extreme temperature events from 1960 to 2020 in Chinese cities. iScience. **27** (3), 109066, **2024**.
12. SHINDELL D., SMITH C.J. Climate and air-quality benefits of a realistic phase-out of fossil fuels. Nature. **573**, 408, **2019**.
13. WEST J.J., SMITH S.J., SILVA R.A., NAIK V., ZHANG Y., ADELMAN Z., FRY M.M., ANENBERG S., HOROWITZ W., LAMARQUE J. Co-benefits of mitigating global greenhouse gas emissions for future air quality and human health. Nature Climate Change. **3**, 885, **2013**.
14. KINNEY P.L. Interactions of climate change, air pollution, and human health. Current Environmental Health Reports. **5**, 179, **2018**.
15. GONÇALVES A.C.R., COSTOVA X., NIETO R., LIBERATO M.L.R. Extreme weather events on energy systems: A comprehensive review on impacts, mitigation, and adaptation measures. Sustainable Energy Research. **11**, 4, **2024**.
16. JIANG L., YANG Y., WU Q., YANG L., YANG Z. Hotter days, dirtier air: The impact of extreme heat on energy and pollution intensity in China. Energy Economics. **130**, 107291, **2024**.
17. PERERA A.T.D., NIK V.M., CHEN D., SCARTEZZINI J., HONG T. Quantifying the impacts of climate change and

extreme climate events on energy systems. Nature Energy. **5**, 150, **2020**.
18. CHINA METEOROLOGICAL ADMINISTRATION. China Climate Bulletin 2024. Available at: https://www.cma.gov.cn/2011xwzx/ 2011xqxxw/2011xqxyw/202502/t20250228_6886278.html. Accessed on 7 March 2025, **2025** [In Chinese].
19. MINISTRY OF ECOLOCY AND ENVIRONMENT OF CHINA. Ministry of Ecology and Environment announces national ambient air quality conditions for December and January-December 2024. Available at: https://www.mee.gov.cn/ywdt/xwfb/ 202501/t20250124_1101318.shtml. Accessed on: 7 March 2025, **2025** [In Chinese].
20. GUO K., JI Q., ZHANG D. A dataset to measure global climate physical risk. Data in Brief. **54**, 110502, **2024**.
21. WEI J., LI Z., GUO J., SUN L., HUANG W., XUE W. FAN T., CRIBB M. Satellite-derived 1-km-resolution PM1 concentrations from 2014 to 2018 across China. Environmental Science & Technology. **53** (22), 13265, **2019**.
22. WEI J., LI Z., XUE W., SUN L., FAN T., LIU L., SU T., CRIBB M. The ChinaHighPM10 dataset: generation, validation, and spatiotemporal variations from 2015 to 2019 across China. Environment International. **146**, 106290, **2021**.
23. WEI J., LI Z., LI K., DICKERSON R., PINKER R., WANG J., LIU X., SUN L., XUE W., GRIBB M. Full-coverage mapping and spatiotemporal variations of ground-level ozone (O3) pollution from 2013 to 2020 across China. Remote Sensing of Environment. **270**, 112775, **2022**.
24. WEI J., LI Z., WANG J., LI C., GUPTA P., CRIBB M. Ground-level gaseous pollutants (NO_2, SO_2, and CO) in China: daily seamless mapping and spatiotemporal variations. Atmospheric Chemistry and Physics. **23**, 1511, **2023**.
25. DONG X., WANG C., ZHANG F., ZHANG H., XIA C. China's low-carbon policy intensity dataset from national- to prefecture-level over 2007-2022. Scientific Data. **11**, 213, **2024**.
26. YANG G., ZHANG G., CAO D., GAO X., WANG X., YANG S., JIANG P., ZHA D., SHAN Y. A comprehensive city-level final energy consumption dataset including renewable energy for China, 2005-2021. Scientific Data. **11**, 738, **2024**.
27. MATERIA S., GARCÍA L.P., VAN STRAATEN C., O S., MAMALAKIS A., CAVICCHIA L., COUMOU D., DE LUCA P., KRETSCHMER M., DONAT M. Artificial intelligence for climate prediction of extremes: State of the art, challenges, and future perspectives. WIREs Climate Change. **15** (6), e914, **2024**.
28. GUO L., FANG M., LIU L., CHONG H., ZENG W., HU X. The development of disaster preparedness education for public: A scoping review. BMC Public Health. **25**, 645, **2025**.
29. RYAN B., JOHNSTON K.A., TAYLOR M., MCANDREW R. Community engagement for disaster preparedness: A systematic literature review. International Journal of Disaster Risk Reduction. **49**, 101655, **2020**.
30. GIRÓN A. China's global energy projects and finance. Journal of Economic Issues. **59** (2), 550, **2025**.
31. ROY J., GHOSH D., GHOSH A., DASGUPTA S. Fiscal instruments: Crucial role in financing low carbon transition in energy systems. Current Opinion in Environmental Sustainability. **5** (2), 261, **2013**.
32. ZHANG Y., ZAHOOR Z. The role of energy subsidies, savings, and transitions in driving energy transformations toward net-zero emissions. Energy. **320**, 135209, **2025**.
33. FU B., LIU Y., MEADOWS M.E. Ecological restoration for sustainable development in China. National Science Review. **10** (7), nwad033, **2024**.
34. ZHANG Y., ZHAO X., GONG J., LUO F., PAN Y. Effectiveness and driving mechanism of ecological restoration efforts in China from 2009 to 2019. Science of the Total Environment. **910**, 168676, **2024**.
35. ATTÍLIO L.A. Spillover effects of climate policy uncertainty on green innovation. Journal of Environmental Management. **375**, 124334, **2025**.
36. NIU S., ZHANG J., LUO R., FENG Y. How does climate policy uncertainty affect green technology innovation at the corporate level? New evidence from China. Environmental Research. **237**, 117003, **2023**.
37. YANG K., CHEN G., CHEN R. The dark side of climate policy uncertainty: Hindering energy transition by shaping environmental taxes effectiveness. Journal of Environmental Management. **369**, 122314, **2024**.
38. WANG J., LIU Y., WANG W., WU H. Does artificial intelligence improve enterprise carbon emission performance? Evidence from an intelligent transformation policy in China. Technology in Society. **79**, 102751, **2024**.