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Measuring the recycling potential of industrial waste for long-term sustainability

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Industrial waste is the byproduct of many industrial processes. Estimating the recycling potential of industrial waste can help solve the anthropogenic circularity conundrum. Here we employed the Environmental Kuznets Curve (EKC) to verify GDP as a route to "amplified resource efficiency". The results provide substantial evidence for an inverted U and N relationship between the hypothesized GDPPC and industrial waste generation. During 2011–2025, the recycling potential in China showed a downward trend. China is projected to experience a dramatic increase in the production of industrial hazardous waste until the successful implementation of industrial hazardous waste prevention measures reverses the current trends. The turning point of the EKC between industrial waste generation and economic development is around US$8000, while the comprehensive utilization is 102.22 million tons. The EKC inflection points established by the study are correlated with the waste category's turning point. The revised EKC claims that technological change may accelerate the turning points; thus, the graph shifts downward and right. The study recommends investing in new technology development to help the industry produce virgin and recycled industrial waste for a circular economy. Recycling potential evaluation also assists us to achieve our Sustainable Development Goals (SDGs).

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Introduction

In the Anthropocene era, material flow from the lithosphere to the anthroposphere caused the rapid depletion of geological minerals and serious pollution of the ecological environment, resulting in the dramatic generation of solid waste. The majority, <90%, of material is sinking finally as waste, yet it could potentially be recycled (Zeng and Li, 2018). Industrial waste is one offspring of anthropogenic metabolism as the global population has grown and become more urban and affluent in the past century. China's industrial waste generation, which includes tailings, sludge, slag, and coal tar, increased tenfold between 1998 and 2018 and is expected to double by 2025 (Hoornweg et al., 2013; Kanwal et al., 2022). China, for example, generated around 3.5 billion tons (t) of industrial waste in 2019, accounting for ~30% of all solid waste generated globally (Kanwal et al., 2021; Kanwal et al., 2022). Global average special waste (i.e., industrial waste) is expected to rise to 12.73 kg/capita/day (Kaza et al., 2018; Wang et al., 2000). These statistics introduce significant challenges which may be addressed by estimating the recycling potential of industrial waste.

Industrial wastes and byproducts are increasingly used as structural fillers. Secondary materials used in construction include recovered rocky or earthy waste materials and industrial byproducts. Slags from the steel industry (used in coastal protection, highways, and parking lot foundations), ashes from municipal solid waste incineration (used in road construction, noise barriers), and construction and demolition waste (used in foundations, road construction) are only a few examples (Ayres and Ayres, 2002; Dijkstra et al., 2019). Industrial waste quantification and recycling are necessary components of a system-oriented industrial ecology to determine the existence of "new anthropogenic elements".

It is well known that China experienced sustained, rapid industrialization from the late 1970s when economic reform was introduced. Gross Domestic Product Per Capita (GDPPC) has grown nearly 10% yearly. Rapid economic growth enhances living standards and social welfare while creating severe environmental problems. According to the central baseline scenario modeled using the OECD ENV-Linkages model, global Gross Domestic Product (GDP) is predicted to quadruple between 2011–2060. As a result, global average per capita income will reach current OECD levels by 2060 (around US$ 40,000) (OECD, 2019). Although waste generation in OECD countries will peak by 2050 and in Asia–Pacific countries by 2075, waste will continue to rise in Sub-Saharan Africa's fast-growing cities. Based on current trends, it is estimated that by 2100, solid waste generation will reach 11 million tons per day, more than three times today's rate (Hoornweg et al., 2013).

There is a correlation between economic growth and municipal/electronic trash; nevertheless, these growths are truly correlated with generation quantity; as a result, an increase in GDP is the cause of an increase in industrial waste generation (D'Adamo et al., 2020). The EKC approach is applied in this study because of its ability to determine the correlation between each social-economic driving factor and solid waste generation. According to the EKC hypothesis, metal consumption peaks and declines throughout economic development. Metals are necessary for economic growth, human progress, and a prerequisite for expanding renewable energy. Metals' anthropogenic use has increased significantly, particularly in emerging economies. As defined by GDPPC, affluence has been recognized as the primary economic driver of domestic metal consumption. On the other hand, domestic metal consumption declines as affluence increases, implying that high-income economies are becoming more resource-efficient (Bechle et al., 2011).

This study can provide a scientific basis for resolving the contradiction between the rapid development of the social economy and the degradation of the ecological environment due to the enormous quantity of industrial solid waste, and thus serve as a guide for ecological environment management decisions regarding waste management in China.

Due to the lack of empirical study on the recent evolution of income distribution and environmental pollution, this essay explores the problem of growing income inequality and environmental degradation (waste generation) to reassess the Kuznets theory from a Chinese viewpoint. The novelty/significance of this research is:

- Currently, we focus on fiscal development and industrial waste generation nexus.
- Despite being part of industrial ecology, waste sector research is patchy. "The United Nations Sustainable Development Goal 12 focuses on waste management and is part of the anthropogenic circularity debate.
- To our knowledge, this is the first observational analysis modeling the Kuznets curve: the income–pollution link across China while also accounting for additional control variables such as population, comprehensive utilization, and mineral rent (% of GDP) and therefore, our analysis results in more appropriate policy prescriptions.

This paper is based on a comprehensive analysis of China's industrial hazardous waste recycling potential (see Fig. S1). The article proceeds as follows. The first two sections describe the conceptual underpinnings of EKC and its integration with the STIRPAT model, current knowledge, methods, and data employed. The third segment discusses the factors contributing to industrial waste and formulates theories for testing. The fourth section explains the conclusions and the fifth section policy implications.

Literature review

Environmental Kuznets Curve (EKC). Grossman and Krueger's (1995) EKC theory defines the dynamic link between income per capita and the environment (Grossman and Krueger, 1995; Kasioumi and Stengos, 2020). Environmental quality deteriorates during the early phase of economic growth, forming an inverted U-curve. However, the pattern reverses after reaching a particular per capita income threshold (Bank, 1992).

Since the early 1990s, a slew of experiments has looked into two Kuznets-related hypotheses: the inverted U-curve hypothesis and the EKC, to see any potential links (between growth and income redistribution and growth and the environment) (Panayotou, 1993a). Real GDP and GDPPC are the most commonly utilized economic measures in EKC literature, including panel data (Ge et al., 2018; Narayan and Narayan, 2010; Ozcan, 2013) and cross-sectional data (Ahmad et al., 2017; Hill and Magnani, 2002). Nevertheless, the findings of these surveys, carried out mainly in the early 2000s, remain inconclusive (Ota, 2017). Therefore, research using a new time frame and methodology is needed.

Several host studies were conducted to investigate the EKC. Li (2016) conducted an observational analysis of economic development and environmental pollution in Gansu province. The findings revealed that Gansu and the west zone have more complex economic conditions and environmental pollution (Li, 2016). Research on pollution and economic growth of Beijing, Tianjin, and Hebei has shown that these cities are already on the left side of the EKC curve: and a greater emphasis on inverted

U-shaped green construction must be made (Dal Mas et al., 2021; Yuan, 2019).

Since then, observational research into the effect of GDP on potentially mitigating environmental pollution based on the Kuznets curve has progressed. Various countries or territories, sampling periods, pollutants, data sets, and methodologies were used (Boubellouta and Kusch-Brandt, 2020; Dodds et al., 2013; Lieb, 2003; Ota, 2017; Purcel, 2020b; Sarkodie and Strezov, 2019; Van Alstine and Neumayer, 2010). The research linking EKC to materials and industrial waste is smaller than municipal waste and air pollution. Precedent research uses a geographically weighted regression (GWR) model to consider spatial heterogeneity to explain the interactions between environmental performance and economic growth in China (Kim et al., 2018; Madden et al., 2019). Mazzanti and Zoboli (2009) examined empirical evidence for decoupling economic growth and municipal waste output by observing an inverted U-shaped curve to gross domestic savings as a proportion of GDP (Ercolano et al., 2018; Khajuria et al., 2012; Mazzanti and Zoboli, 2009; Mazzanti and Zoboli, 2005). Based on the EKC hypothesis, a study investigates the relationship between environmental pollution and economic growth in Chinese provinces. Waste gas, wastewater, and solid waste as environmental indicators and GDP are used as economic indicator. All these pollutants are U-shaped; it can be explained by an ever-cleaner industrial structure, rapidly increasing investment in environmental protection, and tighter environmental policy (Tao et al., 2008; Xuemei et al., 2011; Yanrong et al., 2011).

Similarly, research on panel data from 258 prefecture-level cities in China from 2003 to 2016 uses an extended stochastic effect on population, wealth, and technology (STIRPAT) regression model with the difference-in-difference (DID) approach to research the impact of waste collection policy and MSW's main socioeconomic variables and the environmental hypothesis of EKC measure. A substantial N, U, or inverted N-shaped curve was observed between the MSW generation and economic growth at the national level. However, the traditional EKC hypothesis has no evidence to support it (Cheng et al., 2020; Gui et al., 2019). For the first time for e-waste of 174 countries, the EKC hypothesis was tested using ordinary least square regression. It includes population, urbanization, industrialization, and electricity access. The results strongly support the hypothesized inverted-U relationship between GDPPC and e-waste per capita worldwide (Boubellouta and Kusch-Brandt, 2021).

However, no preceding research accounts for the industrial waste generation concerning EKC variables. Thus, this EKC-China study covers gaps by offering an essential roadmap to estimate Chinese industrial waste recycling potential.

Data, method, and modeling

Data and variables. To ensure data consistency, we established EKCs using GDP as the economic indicator and tailings (total tailings, Fe tailings, Cu tailings, and Au tailings), smelting slag (ISS, NFSS, RM), coal ash, coal gangue, and industrial byproduct gypsum as environmental indicators between 1993- 2018. This paper's data are derived from the World Bank development indicator, the National Statistical Bureau of China. Table 1 contains descriptive information, including the mean and standard deviation. Table 2 shows the regression and covariance coefficients of various indicators. Our descriptive statistics analysis highlights the need to deal with our data's heterogeneity.

Independent variables. We use GDPPC as an independent variable based on previous studies related to environmental economics. GDPPC square and cube are applied to the regression model to test the EKC hypothesis. Suppose the GDPPC coefficient is positive and statistically significant, and the GDPPC square and cube coefficient is negative and significant. Thus inverted U-shaped relationship between GDPPC and industrial waste per capita is obtained; hence, the EKC hypothesis is tested.

Dependent variables. The dependent variable in our study is the industrial waste generation expressed in million tons per annum. Industrial waste has witnessed exceptionally high growth worldwide over the past few years (Kanwal et al., 2022). Industrial waste from various processes, such as sludge, kiln mud, slags, and ashes, is referred to as industrial waste (JeyaSundar et al., 2020). This variable comprises ten waste categories; based on field surveys, literature reviews, and governmental websites.

Table 1 Descriptive statistics.

Variables	Unit	Mean	Max	Min	Std. Dev
GDPPC	US$	8.00×10^3	1.03×10^4	5.62×10^3	1.55×10^3
Comprehensive utilization	Million tons	5.12	1.86×10^1	3.10×10^{-1}	4.97
Mineral rent	% GDP	7.99×10^{-1}	2.82	3.74×10^{-1}	7.88×10^1
Population	10,000/person	1.36×10^9	1.39×10^9	1.33×10^9	2.10×10^7
Financial Growth	One hundred million Yuan	8.18×10^2	6.82×10^3	9.98×10^2	1.33×10^2

Table 2 Covariance matrix.

Variables	GDPPC/US$	Population (10,000/person)	Comprehensive utilization (Million tons)	Mineral rent (% GDP)	Financial Growth (One hundred million Yuan)
GDPPC/US$	1.04×10^7				
Comprehensive utilization (Million tons)	1.65×10^{12}	3.38×10^{17}			
Mineral rent (% GDP)	1.42×10^4	9.04×10^8	4.65×10^1		
Population (10,000/person)	2.07×10^3	1.56×10^8	6.48	9.13×10^{-1}	
Financial Growth (One hundred million Yuan)	1.02×10^6	1.78×10^{11}	1.13×10^3	1.71×10^2	1.04×10^5

Control variables. Time-series analysis is based on the mathematical EKC model of historical data. It inevitably leads to uncertainty as we do not know whether the historical trends in recycling potential can persist. Nonetheless, contextual factors impact potential demand changes (Schipper et al., 2018). Among these subjective factors, demographic variations, Comprehensive utilization rate, and Mineral rents (% of GDP) significantly influence a particular country's waste resource potential.

Comprehensive utilization rate. The comprehensive utilization stage consists of resource recovery and recycling; for example, the crude oil removed during the treatment stage and the sludge can be used in various ways (Dal Mas et al., 2021). Using EKC analysis, an estimate of China's industrial waste production, primary treatment, extensive recycling, and disposal process was carried out using 2011- 2018 as the time boundary.

Mineral rents (% of GDP). The economic potential of industrial waste is calculated in terms of Mineral rents. The difference between the production value for a mineral stock at world prices and its total production costs (Text S1). The values range from 1.45–16.4 million tons (% of GDP) (2020) (SI excel sheet). Thereby, we use Mineral rents as a control variable to estimate recycling potential. We also assumed that the rise in demand is projected to exceed the Chinese mineral and metal demand, as China has already taken an indispensable position in the mineral industry.

Population. We used the population variants depicted in several World Bank publications (Nations, 2015; Zhang et al., 2017) to forecast recycling potential. Hence, we used 1993 as the base year. Previous research indicates that the growing population increases consumer demand, resulting in environmental degradation. However, a shift in environmental impact per capita is possible (Al Mamun et al., 2014; Boubellouta and Kusch-Brandt, 2020; Ohlan, 2015; Salman et al., 2019). From 2004–2006, there was a positive relationship between population and municipal waste generation per capita in 547 Italian municipalities (Abrate and Ferraris, 2010; Hanif and Gago-de-Santos, 2017). Based on this, we anticipate that population growth would positively impact industrial waste generation.

Financial growth. Given that China is already at a crossroads in expanding financial reform and reducing environmental pollution, it is critical and worthwhile to examine the relationship between financial development and environmental performance in China (Maneejuk et al., 2020; Zhao et al., 2019) (Awasthi et al., 2018). The existing research uses an "investment in environmental pollution treatment" as a financial sector indicator. Therefore, we chose this measure as financial depth. It is expressed as the ratio of total investment to the GDP in percentage terms. Data is collected from China Statistical Yearbook (Book).

Methodology. The Environmental Kuznets Curve (EKC) is used in this study to assess the relationship between social-economic factors and industrial hazardous waste generation and calculate Chinese future recycling potential. By quantitatively assessing the IHW generation trend at a macro level, our study may provide a comprehensive picture of IHW generation and feedback on the Chinese government's efficiency.

EKC modeling. The EKC model is based on the quadratic relationship between GDPPC and the environment. Many factors influence the relationship between the two, so in this paper, we adopt a trinomial equation to establish the quantitative relationship between GDPPC and the generation of industrial wastes. GDPPC is plotted along the horizontal axis, while industrial waste generation is plotted along the vertical axis. After determining the model, we use Origin to perform data fitting analysis.

We chose polynomial regression models (Grossman and Krueger, 1991; Miyama and Managi, 2014; Panayotou, 1993b) because of their robustness in dealing with non-linear data and unobserved distinct heterogeneity variation. Using a quadratic function allows testing the standard EKC hypothesis (i.e., the hypothetical bell-shaped connection between pollution and growth). Furthermore, a quadratic functional form enables an EKC with an N or M shape (Terrell, 2020). In contrast, a higher polynomial order specification, such as the cubic function, allows for multiple pattern modeling (Purcel, 2020a). The formulation of the model is well supported by literature (Enchi Liu et al., 2020; Jie Gu et al., 2020; Kim et al., 2018; Lazar et al., 2019; Tao et al., 2008; Xuejiao Huang et al., 2020; Xuemei et al., 2011). The model takes the following form:

$$R_p = \psi + \alpha_0 \gamma^1 + \delta \tag{1}$$

$$R_p = \psi + \alpha_0 \gamma^1 + \alpha_1 \gamma^2 + \delta \tag{2}$$

$$R_p = \psi + \alpha_0 \gamma^1 + \alpha_1 \gamma^2 + \alpha_2 \gamma^3 + \delta \tag{3}$$

where R_p is the recycling potential index for industrial waste, ψ is the intercept value, γ is the economic development index (GDPPC), α_0, α_1, α_2 is the parameter to be estimated, δ is the random error term. The paper uses third-order polynomial fitting curves to have a higher fit, and R^2 and F tests show excellent results. The alpha coefficients determine the precise functional form as follows:

$\alpha \neq 0$, $\alpha_0 = \alpha_1 = 0$: the linear relationship between industrial waste and growth

$\alpha_0 < 0$, $\alpha_1 > 0$, $\alpha_2 = 0$: U-shaped industrial waste growth nexus

$\alpha_0 > 0$, $\alpha_1 < 0$, $\alpha_2 = 0$: inverted U-shaped industrial waste growth nexus

$\alpha_0 > 0$, $\alpha_1 < 0$, $\alpha_2 > 0$: N-shaped industrial waste growth nexus

$\alpha_0 < 0$, $\alpha_1 > 0$, $\alpha_2 < 0$: inverted N-shaped industrial waste growth nexus

An EKC-STIRPAT Model. STIRPAT is a well-known model in ecology; it is a mathematical expansion of the classic IPAT model. The model employs driving factors to assess the impact (*I*) of human activity on the environment (Wang et al., 2017). There are three basic specifications: population (*P*), affluence (*A*), and technology (*T*), usually in non-logarithmic form (Wang et al., 2013). Although this is important for theoretical work, researchers typically estimate using its logarithm version (STIRPAT).

$$\ln I = \mathrm{a} + \mathrm{b} \ln P + \mathrm{c} \ln A + \mathrm{d} \ln T + \mathrm{e} \tag{4}$$

Here, representative pollutants industrial hazardous waste emissions were selected as *I* indicators, and the indicators of the social economy were selected as *P* (Population/10000 persons), *A* (Affluence GDPPC), and *T* (Energy intensity by GDP) indicators, while e denotes an error.

Since the relationship between GDP and environmental degradation might be non-linear, the STIRPAT model has been used to investigate the EKC hypothesis between GDP and emissions (CO_2) or other environmental indicators. This has yet to be tested for solid waste. Combining the EKC hypothesis with the STIRPAT model could give a powerful technique for

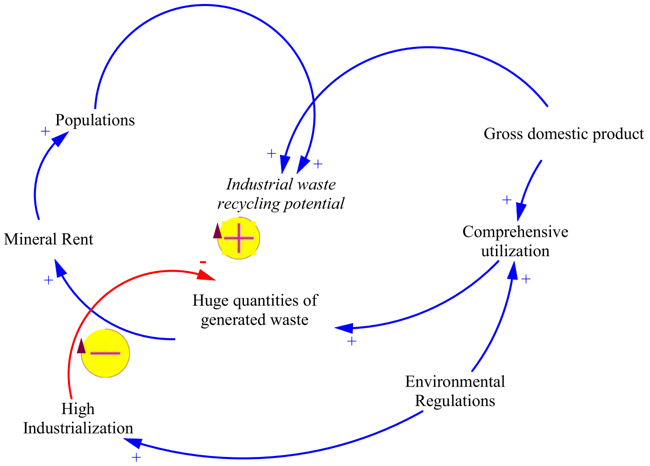


Fig. 1 Diagram of the model's causal loops. Bold lines represent a ± feedback mechanism among variables.

investigating the relationship between GDP and waste quantity in each industrial hazardous waste category.

Results

Interrelationship among strategic elements to support EKC. The schematic view of the model is illustrated in Fig. 1 (produced with Vensim PLE 9.0 software). Considering the feedback loop between waste generation variables and GDP is valuable. The model allows us to evolve industrial waste recycling potential in non-trivial ways: including economics, comprehensive utilization, mineral rent, waste generation intensity, and environment. Industrialization also leads to the accumulation of waste pollutants. Growing ecological footprints and poor environmental cleanup bring about indirect EKC support. Without proper regulation, the link between the environment and development may constantly be positive. Moreover, Fig. 1 implies that China's desire for a healthy climate increases the government's pressure to regulate industry-based waste effectively.

Model equations. Numerous EKC research formulae, including linear, quadratic, and cubic, ensure the chosen model's accuracy. Polynomial regression analysis revealed the following findings based on the GDPPC and the "three wastes" emission data statistics (Table S1).

Model analysis. In order to ensure the cross-compatibility of waste generation data and to develop forecasts for waste recycling potential, this analysis assumes that waste generation grows predominantly due to two variables. GDPPC growth: As a country develops economically, its per capita waste generation rises. GDPPC, with a purchasing power parity adjustment to 2011, shows economic growth. Population growth: as a country's population increases, its total waste output rises proportionally. Figure 2 depicts the observed relationship between GDPPC and waste generation. The correlation between GDPPC and waste generation (tons/person/year) was calculated using a regression model. Total tailings and total slag (1993–2018) showed an inverted N shape, while different types of tailings, such as coal ash, coal gangue, etc., showed an inverted U shape. The independent variable in the best-fitting model is the natural logarithm of GDPPC (see STIRPAT model), while the dependent variable is per capita waste generation in tons/person/year.

The Chinese EKC for the industrial waste generation curve is in the upward phase of the inverted U. Subsequently, large quantities of industrial waste, such as coal tar, different types of tailings, and slag, have increased quickly in recent years. At the same time, it demonstrates the influence of the Chinese GDPPC and the absence of timely environmental policy implementation. Numerous Kuznets curves were fitted to environmental and economic data to get regression coefficients R^2 (Fig. 2). The model's R^2 for the trinomial equation is 0.86; the F test shows significance. Because the regression value is close to 1, the degree of curve fitting is more significant, and the analytical error is small. We compare our value to the volume of e-waste collected and the GDP Purchasing Power Standards, and the findings indicate that the best fit for the data is possible (Awasthi et al., 2018; D'Adamo et al., 2020).

STIRPAT model. This paper defines $\ln PRV$, $\ln PPV$, $\ln ARV$, lnAPV, $\ln TPV$, and $\ln TRV$ as dependent variables I. $\ln GDP$, $\ln P$, $\ln T$ (Energy intensity by GDP) are defined as independent variable PAT. It can be seen that the R^2 of all four groups of equations is more significant than 0.957, indicating that the regression results are credible. The three indexes with the greatest impact are as follows: $\ln PRV$ (11.845), $\ln ARV$ (−0.0069), and $\ln TRV$ (0.19062) (Fig. 3). Perhaps the most important lesson to be learned from the obtained estimates is that reducing the amount of industrial waste generated is a collaborative effort, as environmental measures taken by one municipality in the region affect the concentration levels of the pollutant in neighboring municipalities. The implications of the above model are to evaluate anthropogenic environmental impacts and constitute a valuable instrument for policy decision-making directed at controlling hazardous pollutants.

EKC analysis and variable fitting. Economic development probably gives rise to environmental degradation, promoting economic prosperity with environmental protection. The EKC principle states that as the economy grows, so do emission indicators and the human population. Figure 4 shows the turning point for each variable, like comprehensive utilization in 2019 has a turning value of 102 million tons (Table S2). The waste category's turning point corresponds to the study's determined EKC inflection points. The revised EKC claims that technological change may accelerate the turning points; thus, the EKC graph shifts downward and right.

The EKC turning points. During 2000–2018, the economy in China rapidly grew with an average increasing rate of 7.6% [Fig. S3A]. For each measure of financial development, there is a range of GDPPC for which the total elasticity of financial development on industrial waste discharge per capita is negative [SI Fig. S3B]. In other words, financial development benefits environmental quality at a particular degree of development. One explanation for this observation is that financial development's effects on technological progress are critical for improving energy efficiency and lowering the waste emission intensity (i.e., the ratio of waste generation to GDP), which is not linear and depends on the economy's specific characteristics.

The Chinese economy proliferated due to policies that allowed industrialization to dominate the economy. The turning point of the EKC between industrial waste generation and economic development in China is US$ 8066 (2018) (Fig. 4). The waste generation will continuously reduce as GDPPC increases if China's economic growth is maintained. The underlying empirical research paid close attention to turning points in the waste generation-economic development nexus. Existing research

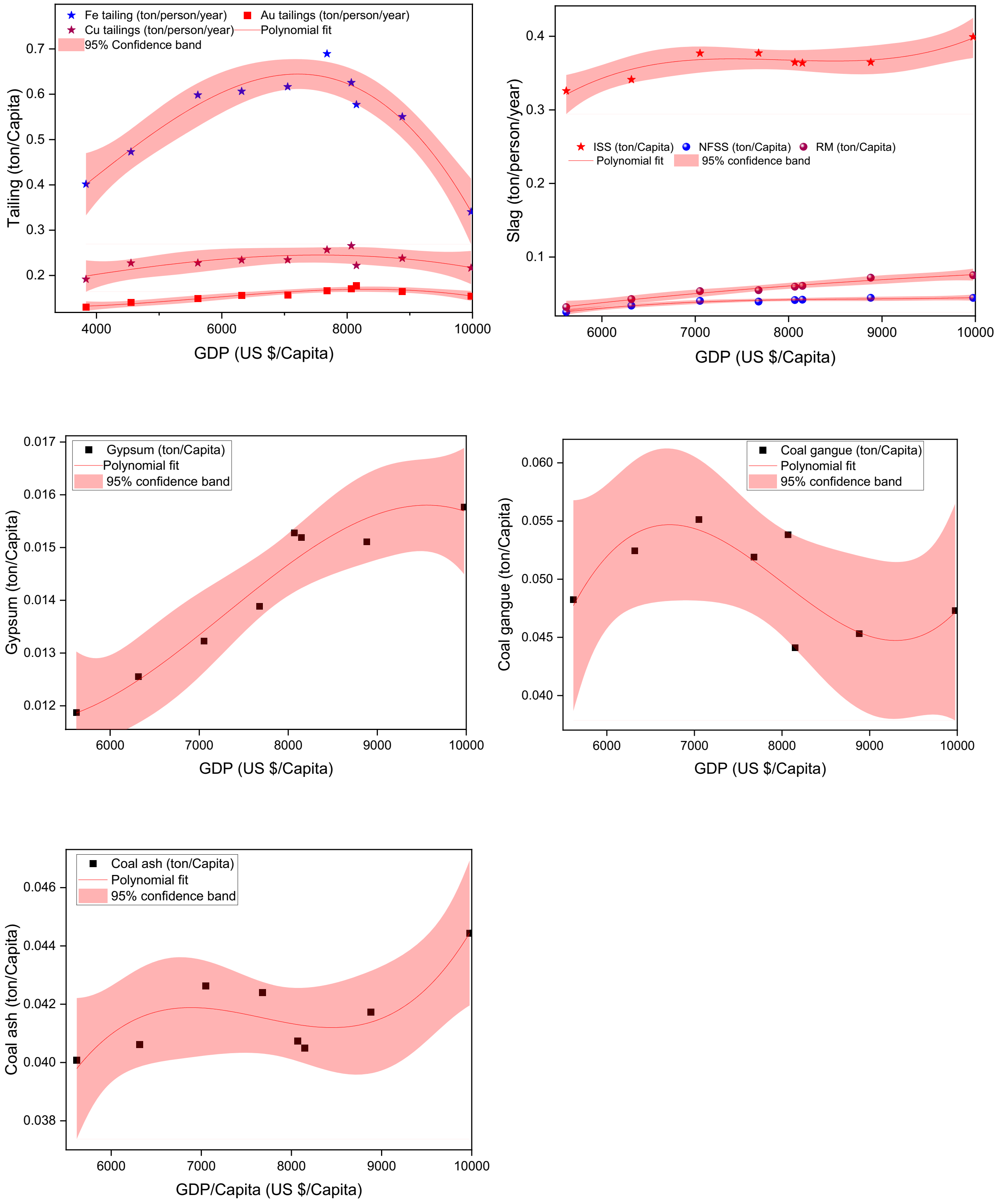
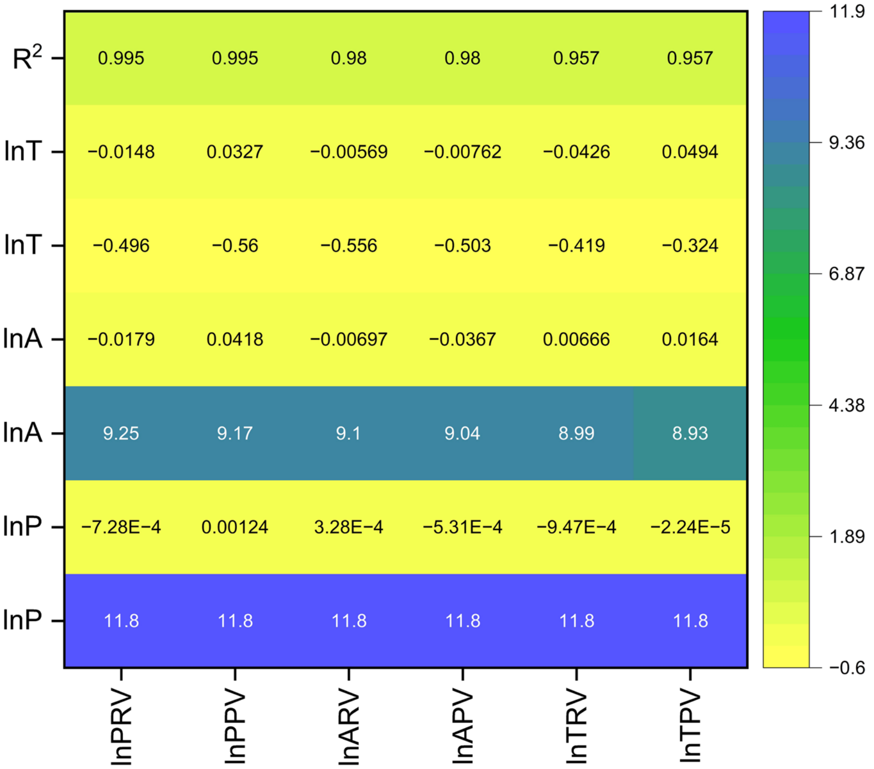


Fig. 2 Industrial waste generation and GDPPC nexus graph. It shows the GDPPC relationship, which steadily rises and correlates to industrial waste generation. The curves show quadratic regression models fitted to the data.

shows that turning point values depend on various factors, including economic growth, the variables used to proxy for environmental quality, and the model used (Lazar et al., 2019; López-Menéndez et al., 2014; Sulemana et al., 2017). In our analysis, the presence of divergent GDP values for turning points are insulated from these sources of heterogeneity for the same pollutant (industrial waste generation) and after controlling for the same domestic (population, comprehensive utilization) and



	lnPRV	lnPPV	lnARV	lnAPV	lnTRV	lnTPV
R^2	0.995	0.995	0.98	0.98	0.957	0.957
lnT	−0.0148	0.0327	−0.00569	−0.00762	−0.0426	0.0494
lnT	−0.496	−0.56	−0.556	−0.503	−0.419	−0.324
lnA	−0.0179	0.0418	−0.00697	−0.0367	0.00666	0.0164
lnA	9.25	9.17	9.1	9.04	8.99	8.93
lnP	−7.28E−4	0.00124	3.28E−4	−5.31E−4	−9.47E−4	−2.24E−5
lnP	11.8	11.8	11.8	11.8	11.8	11.8

Fig. 3 The STIRPAT model has been used to investigate the EKC hypothesis between GDP and emissions (industrial waste) or other environmental indicators. Here, lnA denotes the log of affluence, lnT the log of technology, and lnP the log of population.

external mineral rent (% of GDP) factors. As a result, disparities in these turning points may well reproduce structural heterogeneity within our sample country.

Chinese EKC. The relationship between social economy and industrial waste pollution varies based on the country's level of development (Levinson, 2002). However, this EKC pattern was most likely triggered by the following: The structure of the Chinese economy has shifted away from energy-intensive heavy industry to a more market-oriented service-based economy, which has aided China in ameliorating rather than exacerbating pollution. Additionally, corporations are committed to investing in new and enhanced technologies to increase cost-effectiveness (Luo et al., 2014; Panayotou, 1993b). One of the most notable implications of this trend has been an increase in resource efficiency (comprehensive utilization) within the industrial sector, which has resulted in a 50% reduction in industrial energy intensity during the 1990s (Liu and Diamond, 2005). In addition, environmental awareness has increased among citizens (Luo et al., 2014). Environmental protection regulations have been enacted and efficiently implemented, another primary reason for impelling EKC (He and Wang, 2012; Kijima et al., 2011).

Numerical model for industrial waste recycling potential. Industrial waste is recycled based on generation volume and unit economic value (Yu et al., 2020). Equation 4 illustrates the quantitative model.

$$RP_{IW} = \sum TGW_a \times EV_a \tag{5}$$

where RP_{IW} refers to the industrial waste recycling potential (unit: US$), and TGW_a refers to the total generated amount (unit: million tons) of industrial $\mathrm{waste}_\mathrm{a}$. EV_a refers to the unit economic value (Chinese Yuan) of different waste categories. This model is well supported by literature (Yu et al., 2020). Table S3 shows the recycling potential in a million tons/yuan from 2011–2017. Then we forecast it till 2025 using integrated ARMA in NumXL software. Figure 5 shows a trend from 2011–2025, and the recycling potential shows a downward trend supporting EKC. For instance, total tailings support an inverted N-shaped. This estimation derives the probability distribution of the waste intensity factor statistically and extrapolates trash tonnages across China. This downtrend of recycling potential is due to the few valuable resources in industrial waste.

We compare our projections result with previously published papers. Hoornweg et al.,2013 stated that extending those forecasts to 2100 for various published population and GDP scenarios demonstrates that global 'peak waste' will not occur this century if current trends continue (Dyson and Chang, 2005; Hoornweg et al., 2013). Li et al. 2020 estimated that the overall volume of discarded foundry sand in the United States declined from 2.2–7.1 million tons in 2004 to 1.4–4.7 million tons in 2014 (Li et al., 2020). Similarly, minerals included in non-hazardous industrial waste (NHIW) account for 100 million tons, with an annual power potential of ~200 billion kWh from 1990 to 2016. Both are predicted to increase by around 50% between 2017 and 2050 (Chen et al., 2021).

Robustness check. The sensitivity analysis with a deviation (±5%) is used to test the robustness of the EKC Model. Figure 6 shows that all the variables in EKC Model have different influence directions, as mentioned in the above model, so the estimation of the model is robust and reliable. We also validated our prediction with Integrated ARMA. Sarkodie and Strezov, 2018 used autoregressive distributed lag (ARDL) analysis to validate the inverted N-shaped EKC hypothesis (Barış-Tüzemen et al., 2020; Sarkodie and Strezov, 2018).

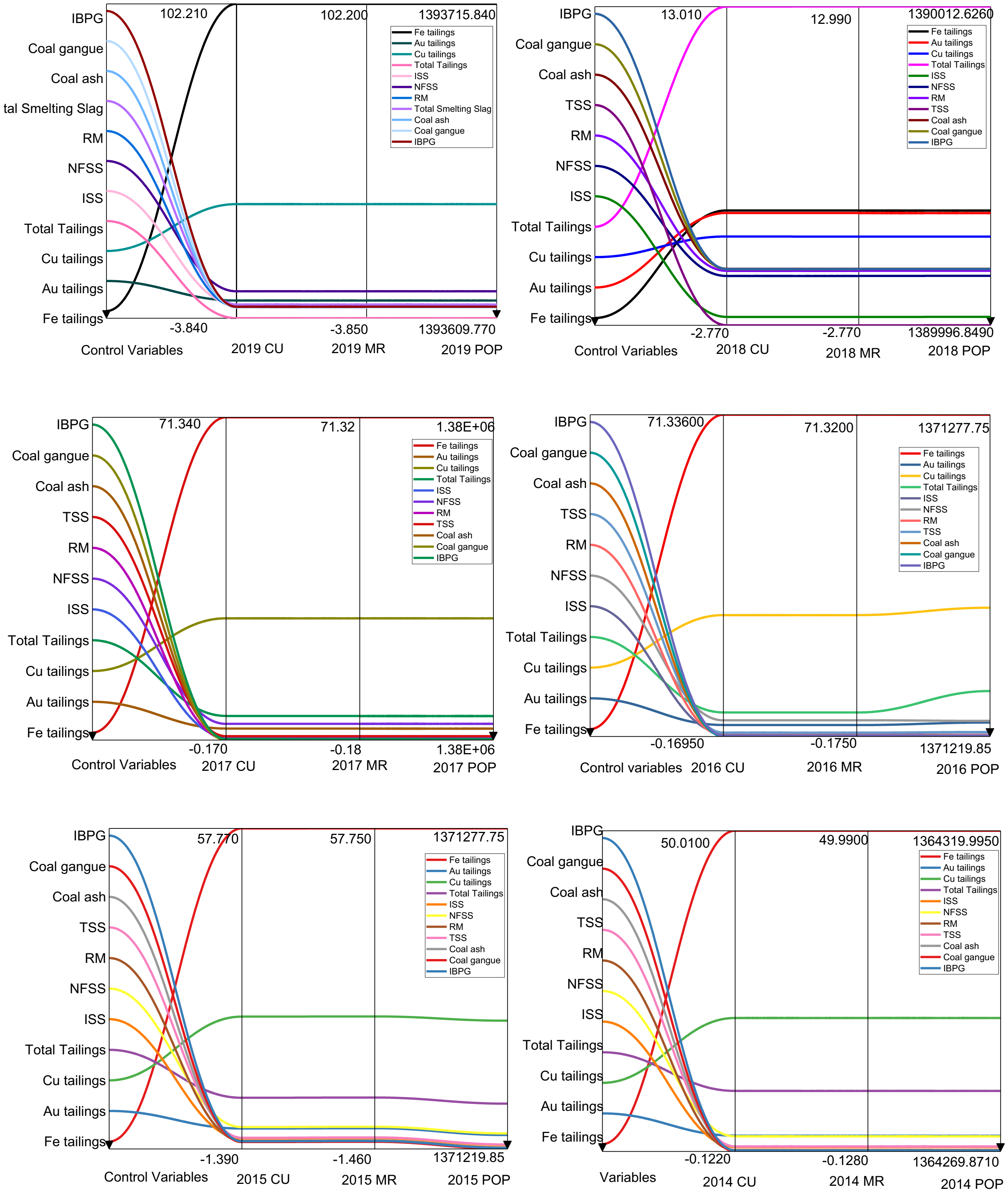


Fig. 4 Continued.

Discussion

The amount of waste generated and economic activity determines industrial waste recycling potential toward anthropogenic circularity. This paper closes the gap by establishing a sound framework to analyze industrial waste-related trends within a WKC conceptual framework encompassing the policy evaluation stage. The WKC theory was tested, and adding control variables demonstrated its robustness. The GDPPC, coal ash, and coal gangue showed an inverted U-curve, while total tailings, slag, and the industrial byproduct gypsum showed an inverted N-curve. The Chinese data set reflects signs of decoupling (reversal of industrial waste discharge per capita),

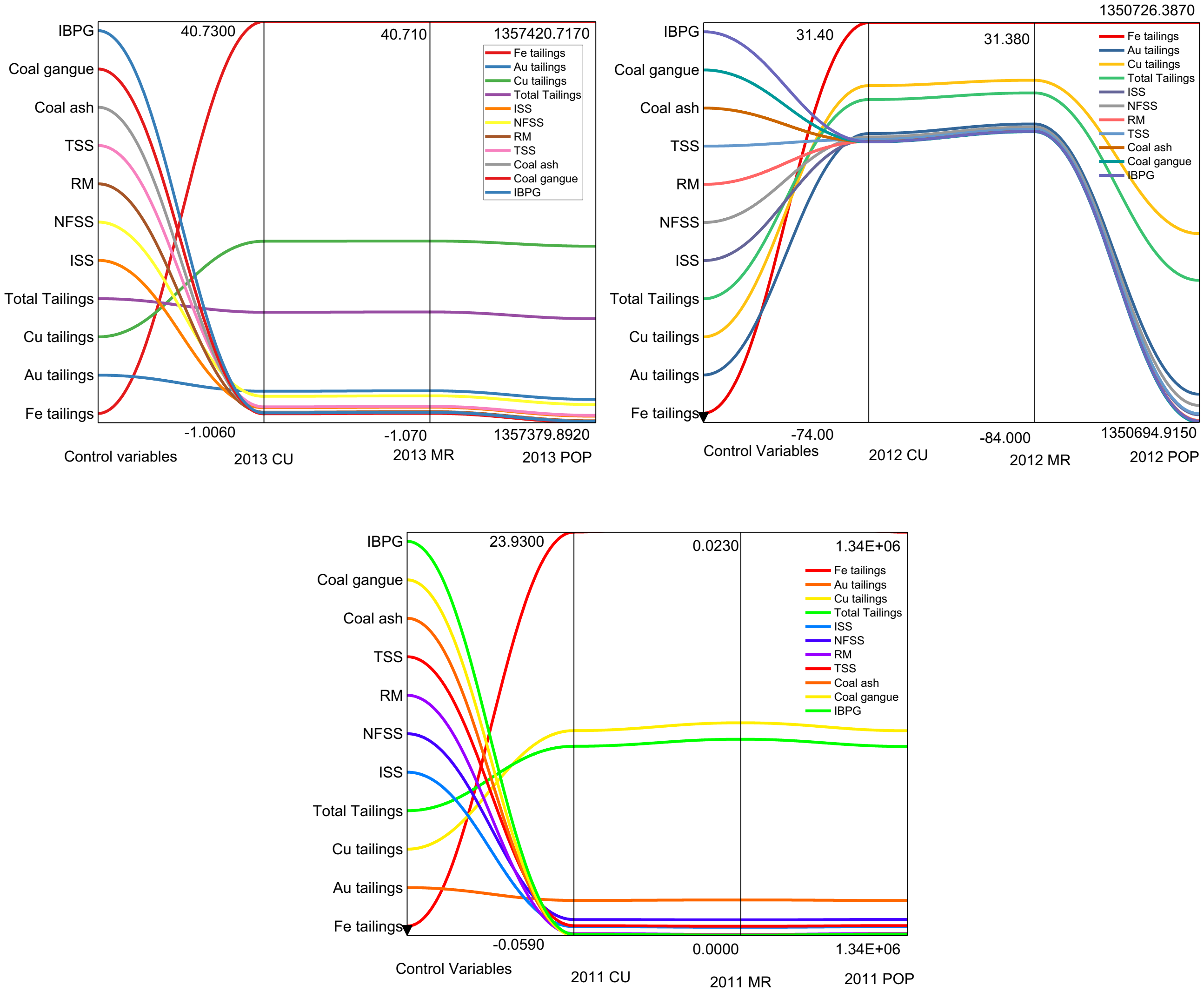


Fig. 4 EKC turning point for different control variables. The existence of EKC in industrial waste can also be checked graphically.

indicating that the EKC of industrial waste per capita is still inverted N-curve due to the comprehensive utilization rate. The annual growth of China's GDPPC in the 5 years leading up to the study appeared to play a significant role in the rise of industrial waste.

Thus, Chinese EKC exists in industrial waste, i.e., industrial waste generation increases as GDPPC rises and then starts declining at a certain level of GDPPC. However, this study determined the turning point at a high GDP level of US$ 8066 ± 1836 per capita. The turning point estimated in this work is consistent with Sarkodie and Strezov, who found US $7078 in 2018 (Sarkodie and Strezov, 2018). In EKC, the recycling rates generally remain high throughout. Thus, the proportion of industrial waste impacted recycling potential positively. The paper presents sound conclusions and recommendations. Building on the current literature overview, future work might include a meta-analysis to better understand the industrial waste-economic nexus via the EKC. Ecological changes cannot depend solely on the environment's automaticity in economic development. Advanced technologies will increase resource utilization, resulting in industrial waste reduction. Thus, the relationship between Chinese GDPPC and industrial waste is constantly changing. The model indicates that industrial waste generation increases in lockstep with GDPPC growth.

Policy implications to achieve a circular economy. Economic liberalization and other growth-oriented measures are not a replacement for environmental policy. Economic growth depends on inputs (environmental resources) to outputs (product waste) (Arrow et al., 1995). EKC's structure is determined by various factors, including the economic institutions that govern human activity. Only highly developed countries are expected to reach a turning point. Policy management, control, and monitoring will become increasingly important for long-term sustainable growth. From 2016–2020, China's yearly growth rate is predicted to be less than seven percent (Zhang et al., 2016), a much slower pace than in the previous three decades. The Chinese government's primary economic goal has switched from expansion to growth-balancing economic activity and environmental protection. Empirical evidence from EKC requires policymakers to understand if economic and sustainable development are stirring simultaneously.

An adequate waste management system will minimize mismanaged waste and generate financial returns by recycling

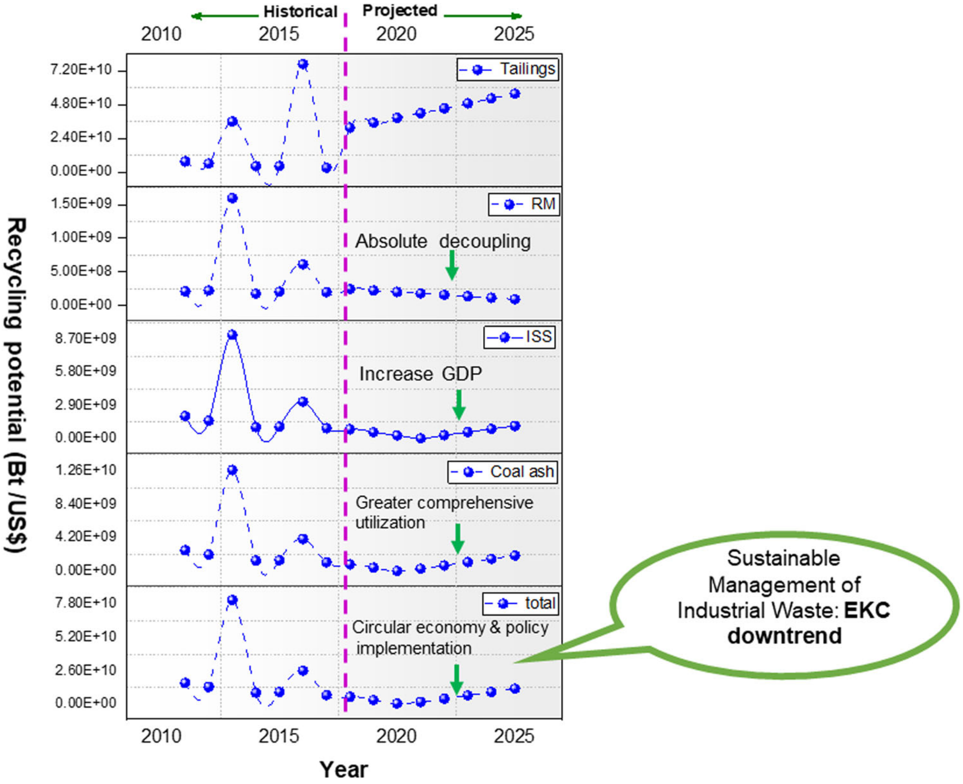


Fig. 5 Recycling potential of industrial waste in the Chinese system. Recycling potential up to 2017 was calculated on collected data (Table S3). The projected forecast is based on the current trend (followed by EKC downtrend). Future recycling capacity of industrial waste will be determined by a range of socioeconomic factors that are difficult to predict.

and reusing materials. The Circular Economy can contribute to several different SDGs. Continued efforts are needed in all countries to improve waste collection, recycling, and reuse. The sustainability bottleneck is necessary to respond to China's complexities and unique challenges of different waste flows. Offering targeted incentives to the private sector and improving national regulations are two factors that may contribute to developing the legal and institutional structure for proper waste management. Our findings help policymakers and academics devise research methods and evaluate the recycling potential of industrial waste.

Based on the preceding study, China's industrial waste management might employ many CE practices to help achieve some SDG 12 goals. In the context of China, the responsible management of chemicals and waste (Target 12.4), the reduction of waste generation (Target 12.5), and the expansion of technological capacity (Target 12.6) are being pursued. In addition, lifecycle methods (Targets 12.4–12.6) and economic and social challenges merit additional consideration in promoting SDG 12. As an added measure, we must disseminate recycling procedures and technology that eliminate chemical emissions harmful to the environment. This would help get us closer to target 12.4 ("By 2020, achieve environmentally sound management of chemicals and all wastes throughout their life cycle."). Urgent initiatives are required for the successful execution of the Chinese Circular Economy Action Plan and the achievement of UN SDG Target 12.4:

- Facilitate collaboration and involvement of all key actors along the whole life cycle of chemicals and materials with transparent supply chain management towards a unified vision based on the 12 principles of circular chemistry at the national, continental, and global levels.
- Implement funding for new technology research to assist the industry in producing virgin and recycled industrial waste efficiently suitable for a circular economy model.
- Waste must be included in future nexus studies to understand better these ties, especially in feedback and dynamics from interconnections between different SDGs.
- Focusing on SDG 13 (Climate Action) is crucial for effective industrial waste recycling. According to Climate Action Tracker, initiatives that invest in green energy infrastructures, such as energy efficiency and low and zero-carbon energy supply technologies, have the highest impact on cutting emissions, regardless of whether the economy recovers optimistically or pessimistically by 2030.
- Guarantee that everyone can access appropriate, safe, affordable solid waste collection services. Often, uncollected waste is dumped in waterways or burned in the open air, resulting in direct pollution and contamination.
- Optimizing waste collection, source segregation, treatment technology, and landfill diversion is vital. Using the Internet of Things to manage and monitor waste saves CO_2 emissions. This will help mitigate climate change.

Here some policy suggestions are tentatively made. Green development of traditional industries should focus on the inherent requirements of "green, circular, and low-carbon" development. Using the "polluter pays" principle, pollution fees (taxes) are levied to increase non-green. Use the guiding role of the capital market to build a green financial system. Briefly, China should develop a plan to maximize the benefits of waste

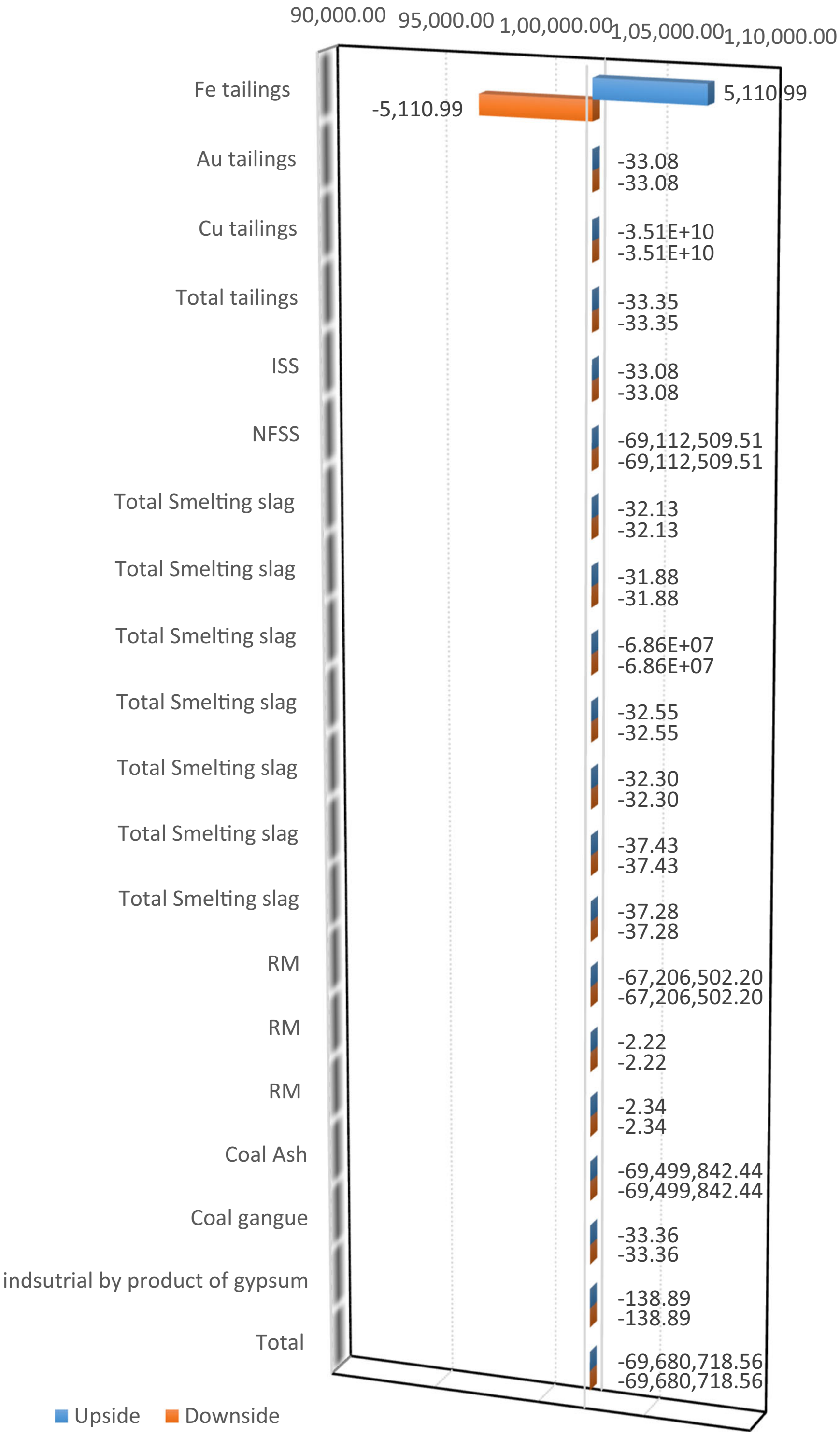


Fig. 6 A tornado diagram is used to compare the relative importance of factors. All unknown parameters are at their base values, as indicated by the grey vertical line. The width of the bars represents the degree of uncertainty associated with each parameter (ranging from lower to upper limit). The blue segments of the bars indicate result values that increase the base case. In contrast, the orange segments indicate result values that decrease the base case.

comprehensive utilization technology transfer and resource recovery technology.

Limitations. Our analysis yielded novel insights into the significant determinants of industrial waste and contributed to the EKC's analytical discussion. Due to the limitation of the original data, the time series samples are only taken from 1993–2018 (and, for fewer cases, 2011–2018). Thus, the sample size is small; the empirical analysis is often more relevant if we use quarterly or monthly data. When additional data sets spanning many years become accessible, we allow prospective studies to use more extensive data sets covering a more extended period. Additionally, we urge future experiments to use various explanatory variables and other techniques to account for time-invariant characteristics.

Data availability

The supported data sources are publicly available, and their citations are mentioned in references of this paper and the Supplementary Information file.

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References

Abrate G, Ferraris, M (2010) The environmental Kuznets curve in the municipal solid waste sector. HERMES 1:1–28

Ahmad N, Du L, Lu J, Wang J, Li H-Z, Hashmi MZ (2017) Modelling the CO_2 emissions and economic growth in Croatia: is there any environmental Kuznets curve? Energy 123:164–172

Al Mamun M, Sohag K, Mia MAH, Uddin GS, Ozturk I (2014) Regional differences in the dynamic linkage between CO_2 emissions, sectoral output and economic growth. Renew Sust Energy Rev 38:1–11

Arrow K, Bolin B, Costanza R, Dasgupta P, Folke C, Holling CS, Jansson B-O, Levin S, Mäler K-G, Perrings C (1995) Economic growth, carrying capacity, and the environment. Ecol Econ 15:91–95

Awasthi AK, Cucchiella F, D'Adamo I, Li J, Rosa P, Terzi S, Wei G, Zeng X (2018) Modelling the correlations of e-waste quantity with economic increase. Sci Total Environ 613:46–53

Ayres RU, Ayres L (2002) A handbook of industrial ecology. Edward Elgar Publishing, UK

Bank W (1992) World development report: Development and the environment. World Bank

Barış-Tüzemen Ö, Tüzemen S, Çelik AK (2020) Does an N-shaped association exist between pollution and ICT in Turkey? ARDL and quantile regression approaches. Environ Sci Pollut Res 27:20786–20799

Bechle MJ, Millet DB, Marshall JD (2011) Effects of income and urban form on urban NO_2: Global evidence from satellites. Environ Sci Technol 45:4914–4919

Boubellouta B, Kusch-Brandt S (2020) Testing the environmental Kuznets curve hypothesis for E-waste in the EU28+ 2 countries. J Clean Prod 277:123371

Boubellouta B, Kusch-Brandt S (2021) Cross-country evidence on environmental Kuznets curve in waste electrical and electronic equipment for 174 countries. Sustain Prod Consum 25:136–151

Chen J, Li X, Huang K, Eckelman MJ, Chertow MR, Jiang D (2021) Non-hazardous industrial waste in the United States: 100 Million tonnes of recoverable resources. Resour Conserv Recycl 167:105369

Cheng J, Shi F, Yi J, Fu H (2020) Analysis of the factors that affect the production of municipal solid waste in China. J Clean Prod 259:120808

D'Adamo I, Gastaldi M, Rosa P (2020) Recycling of end-of-life vehicles: assessing trends and performances in Europe. Technol Forecast Soc Change 152:119887

Dal Mas F, Zeng X, Huang Q, Li J (2021) Quantifying material flow of oily sludge in China and its implications. J Environ Manag 287:112115

Dijkstra JJ, Comans RN, Schokker J, van der Meulen M (2019) The geological significance of novel anthropogenic materials: Deposits of industrial waste and by-products. Anthropocene 28:100229

Dodds WK, Perkin JS, Gerken JE (2013) Human impact on freshwater ecosystem services: a global perspective. Environ Sci Technol 47:9061–9068

Dyson B, Chang N-B (2005) Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modeling. Waste Manag 25:669–679

Enchi Liu XL, Wendan L, Huqing Y (2020) Analysis of the relationship between industrial waste discharge and per capita GDP in Chengdu—a metrological analysis based on Environmental Kuznets Curve (EKC). Sustain Dev 10:347–356

Ercolano S, Gaeta GLL, Ghinoi S, Silvestri F (2018) Kuznets curve in municipal solid waste production: An empirical analysis based on municipal-level panel data from the Lombardy region (Italy). Ecol Indic 93:397–403

Ge X, Zhou Z, Zhou Y, Ye X, Liu S (2018) A spatial panel data analysis of economic growth, urbanization, and NOx emissions in China. Int J Environ Res Public Health 15:725

Grossman GM, Krueger AB (1995) Economic growth and the environment. Q J Econ 110:353–377

Grossman GM, Krueger AB (1991) Environmental impacts of a North American free trade agreement. https://www.nber.org/papers/w3914

Gui S, Zhao L, Zhang Z (2019) Does municipal solid waste generation in China support the environmental Kuznets curve? New evidence from spatial linkage analysis. Waste Manag 84:310–319

Hanif I, Gago-de-Santos P (2017) The importance of population control and macroeconomic stability to reducing environmental degradation: an empirical test of the environmental Kuznets curve for developing countries. Environ Dev 23:1–9

He J, Wang H (2012) Economic structure, development policy and environmental quality: an empirical analysis of environmental Kuznets curves with Chinese municipal data. Ecol Econ 76:49–59

Hill RJ, Magnani E (2002) An exploration of the conceptual and empirical basis of the environmental Kuznets curve. Aust Econ 41:239–254

Hoornweg D, Bhada-Tata P, Kennedy C (2013) Environment: waste production must peak this century. Nat News 502:615

JeyaSundar PGSA, Ali A, Guo D, Zhang Z, (2020) 6—Waste treatment approaches for environmental sustainability. In: Chowdhary P, Raj A, Verma D, Akhter Y (eds.) Microorganisms for sustainable environment and health. Elsevier, p 119–135

Jie Gu YJ, Lin L, Huqing Y (2020) Analysis of the current situation of Kuznets curve in Fujian province. Sustain Dev 10:338–346

Kanwal Q, Li J, Zeng X (2021) Mapping recyclability of industrial waste for anthropogenic circularity: a circular economy approach. ACS Sustain Chem Eng 9:11927–11936

Kanwal Q, Zeng X, Li J (2022) Drivers-pressures-state-impact-response framework of hazardous waste management in China. Crit Rev Environ Sci Technol 52:2930–2961

Kasioumi M, Stengos T (2020) The environmental Kuznets curve with recycling: a partially linear semiparametric approach. J Risk Financ Manag 13:274

Kaza S, Yao L, Bhada-Tata P, Van Woerden F (2018) What a waste 2.0: a global snapshot of solid waste management to 2050. World Bank Publications

Khajuria A, Matsui T, Machimura T, Morioka T (2012) Decoupling and environmental Kuznets curve for municipal solid waste generation: evidence from India. Int J Environ Sci 2:1670–1674

Kijima M, Nishide K, Ohyama A (2011) EKC-type transitions and environmental policy under pollutant uncertainty and cost irreversibility. J Econ Dyn Control 35:746–763

Kim Y, Tanaka K, Ge C (2018) Estimating the provincial environmental Kuznets curve in China: a geographically weighted regression approach. Stoch Environ Res Risk Assess 32:2147–2163

Lazar D, Minea A, Purcel A-A (2019) Pollution and economic growth: evidence from Central and Eastern European countries. Energy Econ 81:1121–1131

Levinson A (2002) The ups and downs of the environmental Kuznets curve. https://econpapers.repec.org/paper/geoguwopa/gueconwpa~01-01-08.htm

Li JE (2016) Kuznets curve of the relationship between economic growth and environmental pollution in Gansu Province. Econ Res 31:8–9

Li X, Chertow M, Guo S, Johnson E, Jiang D (2020) Estimating non-hazardous industrial waste generation by sector, location, and year in the United States: a methodological framework and case example of spent foundry sand. Waste Manag 118:563–572

Lieb CM (2003) The environmental Kuznets curve: a survey of the empirical evidence and of possible causes. https://www.econstor.eu/bitstream/10419/127208/1/dp391.pdf

Liu J, Diamond J (2005) China's environment in a globalizing world. Nature 435:1179–1186

López-Menéndez AJ, Pérez R, Moreno B (2014) Environmental costs and renewable energy: re-visiting the environmental Kuznets curve. J Environ Manage 145:368–373

Luo Y, Chen H, Zhu QA, Peng C, Yang G, Yang Y, Zhang YJPO (2014) Relationship between air pollutants and economic development of the provincial capital cities in China during the past decade. PLoS One 9:e104013

Madden B, Florin N, Mohr S, Giurco D (2019) Using the waste Kuznet's curve to explore regional variation in the decoupling of waste generation and socioeconomic indicators. Resour, Conserv Recycl 149:674–686

Maneejuk N, Ratchakom S, Maneejuk P, Yamaka W (2020) Does the environmental Kuznets curve exist? An international study. Sustainability 12:9117

Mazzanti M, Zoboli R (2005) Delinking and environmental Kuznets curves for waste indicators in Europe. Environ Sci 2:409–425

Mazzanti M, Zoboli R (2009) Municipal waste Kuznets curves: evidence on socioeconomic drivers and policy effectiveness from the EU. Environ Resour Econ 44:203

Miyama E, Managi S (2014) Global environmental emissions estimate: application of multiple imputation. Environ Econ Policy Stud 16:115–135

Narayan PK, Narayan S (2010) Carbon dioxide emissions and economic growth: panel data evidence from developing countries. Energy Policy 38:661–666

Nations U (2015) World population prospects: the 2015 revision. https://www.un.org/en/development/desa/publications/world-population-prospects-2015-revision.html

OECD (2019) Global Material Resources Outlook to 2060: economic drivers and environmental consequences. OECD, Paris

Ohlan R (2015) The impact of population density, energy consumption, economic growth and trade openness on CO 2 emissions in India. Nat Hazards 79:1409–1428

Ota T (2017) Economic growth, income inequality and environment: assessing the applicability of the Kuznets hypotheses to Asia. Palgrave Commun 3:1–23

Ozcan B (2013) The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: a panel data analysis. Energy Policy 62:1138–1147

Panayotou T (1993a) Empirical tests and policy analysis of environmental degradation at different stages of economic development. International Labour Organization

Panayotou T (1993b) Empirical tests and policy analysis of environmental degradation at different stages of economic development. International Labour Organization

Purcel A-A (2020b) New insights into the environmental Kuznets curve hypothesis in developing and transition economies: a literature survey. Environ Econ Policy Stud 22:585–631

Purcel A-A (2020a) New insights into the environmental Kuznets curve hypothesis in developing and transition economies: a literature survey. Environ Econ Policy Stud 22:585–631

Salman M, Long X, Dauda L, Mensah CN, Muhammad S (2019) Different impacts of export and import on carbon emissions across 7 ASEAN countries: A panel quantile regression approach. Sci Total Environ 686:1019–1029

Sarkodie SA, Strezov V (2018) Empirical study of the environmental Kuznets curve and environmental sustainability curve hypothesis for Australia, China, Ghana and USA. J Clean Prod 201:98–110

Sarkodie SA, Strezov V (2019) A review on environmental Kuznets curve hypothesis using bibliometric and meta-analysis. Sci Total Environ 649:128–145

Schipper BW, Lin H-C, Meloni MA, Wansleeben K, Heijungs R, van der Voet E (2018) Estimating global copper demand until 2100 with regression and stock dynamics. Resour Conserv Recycl 132:28–36

Sulemana I, James HS, Rikoon JS (2017) Environmental Kuznets curves for air pollution in African and developed countries: exploring turning point incomes and the role of democracy. J Environ Econ Policy 6:134–152

Tao S, Zheng T, Lianjun T (2008) An empirical test of the environmental Kuznets curve in China: a panel cointegration approach. China Econ Rev 19:381–392

Terrell TD (2020) Carbon flux and N-and M-shaped environmental Kuznets curves: evidence from international land use change. J Environ Econ Policy 1:155–174

Van Alstine J, Neumayer E (2010) The environmental Kuznets curve. In: Gallagher, Kevin P (ed.) Handbook on Trade and the Environment. Elgar, Cheltenham, p 49–59

Wang P, Wu W, Zhu B, Wei Y (2013) Examining the impact factors of energy-related CO2 emissions using the STIRPAT model in Guangdong Province, China. Appl Energy 106:65–71

Wang S, Zhao T, Zheng H, Hu J (2017) The STIRPAT analysis on carbon emission in Chinese cities: an asymmetric Laplace distribution mixture model. Sustainability 9:2237

Wang W, Jiang J, Wu X, Liang S (2000) The current situation of solid waste generation and its environmental contamination in China. J Mater Cycles Waste Manag 2:65–69

Xuejiao Huang JL, Jian L, Lingsen K, Huqin Y (2020) The research based on Kuznets curve on the relationship between Shanghai economic development and environmental pollution. J Low Carbon Econ 9:147–157

Xuemei H, Mingliang Z, Su L (2011) Research on the relationship of economic growth and environmental pollution in Shandong province based on environmental Kuznets curve. Energy Procedia 5:508–512

Yanrong W, Cuili W, Han W (2011) Research on the quantitative relationship between the generation of industrial solid waste and per capita GDP of Henan Province. Energy Procedia 5:593–597

Yu B, Wang J, Li J, Lu W, Li CZ, Xu X (2020) Quantifying the potential of recycling demolition waste generated from urban renewal: a case study in Shenzhen, China. J Clean Prod 247:119127

Yuan JLSAG (2019) An empirical study on the relationship between environmental pollution and economic growth in Beijing-Tianjin-Hebei: based on the perspective of EKC test. Northern Econ Trade 39:118–120

Zeng X, Li J (2018) Urban mining and its resources adjustment: characteristics, sustainability, and extraction. Sci Sin 48:288–298

Zhang B, Cao C, Hughes RM, Davis WS (2017) China's new environmental protection regulatory regime: effects and gaps. J Environ Manage 187:464–469

Zhang K, Dearing JA, Tong SL, Hughes TP (2016) China's degraded environment enters a new normal. Trends Ecol Evol 31:175–177

Zhao J, Zhao Z, Zhang H (2019) The impact of growth, energy and financial development on environmental pollution in China: New evidence from a spatial econometric analysis. Energy Econ 93:104506

Competing interests

The authors declare no competing interests.

Ethical approval

This research did not require any ethical approval.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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