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EDITED BY

Mohamed R. Abonazel,
Cairo University, Egypt

REVIEWED BY

Ihsan Oluç,
Mehmet Akif Ersoy University, Türkiye
Prabhat Kashyap,
University of Delhi, India

*CORRESPONDENCE

Lei Ding,
✉ dinglei3616028@163.com

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Educational investment, technological innovation, and atmospheric environmental efficiency: evidence from SBM-DEA and quantile regression model

Bei Ji¹, Qiong Zhang², Lingyan Liu³ and Lei Ding^{3*}

¹Party Organization Department, Ningbo Polytechnic University, Ningbo, China, ²International Office, Ningbo Polytechnic University, Ningbo, China, ³Scientific Research Office, Ningbo Polytechnic University, Ningbo, China

Introduction: The scientific measurement of urban atmospheric environmental efficiency is a vital prerequisite for achieving air pollution control and regional green high-quality development.

Methods: Based on the data of 11 cities in Zhejiang Province from 2014 to 2022, this study calculates the synergistic governance environmental efficiency (SGEE) of PM_{2.5} and O₃ from both static and dynamic perspectives. Furthermore, a quantile regression model (QRM) is employed to reveal the impact mechanisms of educational investment and technological innovation on the efficiency.

Results: The results show that: (1) there are significant spatio-temporal variations in the concentrations of PM_{2.5} and O₃ among the 11 cities. The effectiveness of coordinated governance is not significant. (2) The average value of SGEE of PM_{2.5} and O₃ in Zhejiang Province is 0.533. Technological advancement is the primary driving force behind the improvement of the SGEE of PM_{2.5} and O₃. (3) The results of QRM indicate that educational investment primarily improves the SGEE of PM_{2.5} and O₃ at low efficiency stages, while it exerts a certain resource “Crowding-out effect” at high efficiency stages. In contrast, the rise in the level of technological innovation and the transformation and adjustment of industrial structure can effectively promote the improvement of the SGEE of PM_{2.5} and O₃.

Discussion: In the future, it need strengthen the role of technological innovation in improving the SGEE of PM_{2.5} and O₃.

KEYWORDS

synergistic governance environmental efficiency of PM_{2.5} and O₃, data envelopment analysis, quantile regression model, educational investment, technological innovation

1 Introduction

Continuous improving air quality and promoting high-quality economic development are key measures in the fight for blue skies (Li et al., 2024). With the strong push for the battle against air pollution, the environmental air quality in China has shown a steady upward trend. Initial results have been achieved in the synergistic control of PM_{2.5} and

ozone (O₃) (Kong et al., 2024). In 2024, the PM_{2.5} concentration in cities at the prefecture level and above nationwide is expected to be 29.3 μg/m³, a year-on-year decrease of 2.7%; compared to 2019, the national PM_{2.5} concentration has decreased by 19.4%. O₃ concentration has decreased by 2.7% and has remained stable at 144–145 μg/m³ for three consecutive years. Since 2015, the rising trend of ozone has been initially curbed (Yang J. et al., 2025; Yang Z. et al., 2025). Therefore, adhering to precise, scientific, and law-based pollution control, and emphasizing environmental air quality management, are of great significance for achieving high-quality green transformation and development (Wang H. et al., 2025; Shao et al., 2025).

Environmental efficiency characterizes the environmental performance level of production units through the ratio of economic output to environmental impact (Zadmirzaei et al., 2024; Paramati et al., 2022; Song et al., 2012). Atmospheric environmental efficiency (AEE) represents a further deepening and expansion of environmental efficiency in the field of atmospheric environments, which can effectively reflect the comprehensive management level of the atmospheric environment and embody the efficiency of transforming resource input into economic value while managing atmospheric pollution emissions (Fang et al., 2023; Huang et al., 2021).

As the prevention and control of air pollution in China has received widespread attention from society these years, numerous scholars have conducted research on the measurement and evaluation of AEE (Ren et al., 2023; Miao et al., 2019a), specifically including: (1) Indicators for measuring AEE: One category uses inputs such as labor, capital, energy, and land, with GDP as the output indicators and the amount of air pollutant emissions as the undesirable output or input indicators (Fang et al., 2023; Lu et al., 2019; Ding et al., 2019). The other category uses indicators such as the number of pollution control facilities and operational costs as inputs, and the removal rate or amount of air pollutants as output indicators, which are commonly referred to as atmospheric pollution control efficiency (Zhou et al., 2023; Wu et al., 2020; Yang and Li, 2018). The first category takes into account both economic development and environmental governance, providing a more comprehensive reflection of the overall performance in air pollution control (Sueyoshi and Yuan, 2015; Wu et al., 2021). However, the selected indicators for air pollutant emissions or concentrations often rely on traditional metrics such as SO₂, NO_x, PM₁₀, and the rate of good air quality (Wu et al., 2021; Lu et al., 2019; Wang et al., 2017), while lacking efficiency measurements for newer air pollution control targets such as PM_{2.5}, O₃, and VOCs. (2) Measurement methods for AEE: Data Envelopment Analysis (DEA) has been widely applied in the measurement of AEE due to its advantages in handling multiple input and output indicators (Zhou et al., 2023; Song et al., 2012). In terms of specific model construction, existing literature has employed various DEA models, including the traditional DEA model, non-radial directional distance function DEA model (Wang et al., 2017), weighted DEA (Ye and Wang, 2019), dynamic network SBM model (Rashid et al., 2024; Fu et al., 2024), Super-efficiency SBM model (Xu et al., 2024; He et al., 2018), two-stage DEA (Guo et al., 2020) and three-stage slack based measure-data envelopment analysis (SBM-DEA) model (Li et al., 2025; Zhang et al., 2024). Additionally, techniques such as the Malmquist index (Ma et al., 2021), Luenberger index (Miao et al., 2019b), and Global Malmquist-Luenberger index have been used to analyze the dynamic changes in AEE (Lu et al., 2019). (3) Socio-

economic factors influencing AEE: These factors mainly include the level of economic development, population density, environmental regulations, industrial structure, technological level, degree of openness, urbanization level, and the level of digital economy development (Fang et al., 2023; Miao et al., 2019b; Li et al., 2019). The analysis models used are primarily based on ordinary least squares (OLS) regression models, lacking detailed comparative analysis of the varying degrees of influence among the different explanatory variables (Liu H. et al., 2022). Meanwhile, the selected indicators did not take into account potential impacts of variables such as educational investment on pollution control. Existing studies have pointed out that education could achieve ecological benefits not only by improving production methods and technological levels but also by promoting ecological protection and cultivating environmental awareness during the basic education phase (Liu K. et al., 2022; Žalėnienė and Pereira, 2021). It, in turn, could change people's consumption concepts and lifestyles, thereby reducing resource consumption and protecting the air environment (Uralovich et al., 2023). However, an increase in educational investment also lead to a resource "Crowding-out effect" on environmental governance investment to some extent, which could be detrimental to the short-term guarantee of air pollution control (Tao et al., 2022; Underdal, 2010).

In summary, while existing research has made many valuable explorations regarding AEE, there are still several shortcomings. Firstly, most studies use a single pollutant indicator as an undesirable output, without adequately considering the impacts of synergistic control of comprehensive and compound air pollutants (such as PM_{2.5} and O₃). Secondly, the existing literature mainly focuses on static dimensional efficiency and lacks studies that comprehensively measure AEE from both static and dynamic dual dimensions, as well as from a long-term and broad spatial perspective. Lastly, there is a lack of comprehensive examination of the socio-economic influencing factors related to AEE, particularly regarding educational investment and technological innovation at different levels.

Given that PM_{2.5} and O₃ pollution is influenced by various intersecting factors such as natural conditions, economic development, and political factors, scientifically evaluating AEE has become a key measure for improving regional air quality (Mo et al., 2024; Zhou et al., 2023). Therefore, this study focuses on Zhejiang Province, a developed coastal economic region in eastern China. It uses the annual average concentrations of PM_{2.5} and O₃ as undesirable outputs and employs a Slacks-Based Measure (SBM)-Undesirable DEA model that accounts for undesirable outputs to measure urban AEE from 2014 to 2022. Then, a Quantile Regression model (QRM) is used to comprehensively reveal the mechanisms of how educational investment and technological innovation impact AEE, and it proposes governance strategies and recommendations. It aims to provide evidence and decision-making references for the synergistic governance of PM_{2.5} and O₃ in rapidly urbanizing areas.

2 Methodology

2.1 Study area

The study area is selected as Zhejiang Province because it is a typical economically developed province in the southeast coastal region of China, and it represents an area facing dual pressures of economic transformation towards green development and

TABLE 1 Air pollution status in Zhejiang province from 2014 to 2023.

Year	ρ SO ₂ (μg/m ³)	ρ NO ₂ (μg/m ³)	ρ PM ₁₀ (μg/m ³)	ρ PM _{2.5} (μg/m ³)	ρ O ₃ (μg/m ³)	ρ CO (mg/m ³)	Proportion of good days (%)
2014	21	39	78	53	153	1.4	75.5
2015	16	37	70	47	158	1.4	78.2
2016	13	34	63	41	153	1.2	83.1
2017	11	34	61	39	159	1.2	82.7
2018	9	32	56	33	159	1.2	85.3
2019	7	31	53	31	154	1.0	88.6
2020	6	29	45	25	145	0.9	93.3
2021	6	29	47	24	142	0.9	94.4
2022	6	24	43	25	154	0.8	89.3
2023	6	26	46	27	149	0.8	91.3

Data Source: Ecological Environment Status Bulletin of Zhejiang Province from 2014 to 2023.

TABLE 2 Descriptive statistics of variables from 2000 to 2020 in Zhejiang Province.

Variable	Indicator	Variable name	Sample size	Average value	Standard deviation	Minimum value	Maximum values
Input variable	Number of employed	Labor	99	333.47	189.27	69.64	759.68
	Energy consumption	Energy	99	1,060.15	718.60	217.32	3,103.81
	Fixed-asset investment	Investment	99	2,918.74	1,803.32	665.08	8,430.45
Desirable outputs	GDP	PGDP	99	87,148.61	26,590.25	44,263.00	153,922.00
Undesirable outputs	PM _{2.5}	PM _{2.5}	99	36.21	11.69	15.00	65.00
	O ₃	O ₃	99	152.68	17.48	119.00	195.00

environmental governance. In addition, it is also one of the key areas in China for air pollution prevention and control (Fang et al., 2023; Zhang et al., 2023; Lu et al., 2019).

The air quality in Zhejiang Province has improved to some extent (as shown in Table 1) in recent years. For instance, SO₂ and NO₂ have reached the national first-level standard for ambient air quality, while PM₁₀ has met the national second-level standard (Xia et al., 2020). However, the ongoing improvement of air quality across the province has become increasingly challenging. The concentration of PM_{2.5} remains relatively high and shows some signs of rebound, especially during the spring and winter seasons. Meanwhile, the Hangzhou Bay area (including Hangzhou, Huzhou, Jiaxing, and Shaoxing) has a high proportion of days with O₃ exceeding the standard, making it the primary pollutant affecting the improvement of urban ambient air quality (Ding et al., 2024). Thus, focusing on the two pollutants, PM_{2.5} and O₃, can provide a more accurate assessment of the urban air pollution situation. Besides, existing studies that use conventional pollutants such as SO₂, NO₂, and PM₁₀ for measuring and assessing AEE cannot accurately reflect the current environmental quality status and lead to an overestimation of the efficiency values. It highlights the

need to scientifically the regional atmospheric environmental efficiency by constructing a new indicator for undesirable outputs (PM_{2.5} and O₃).

2.2 Data sources

This study employs labor, capital, and energy as input indicators, regional Gross Domestic Product (GDP) as the output indicators (Fang et al., 2023; Lu et al., 2019), and PM_{2.5} and O₃ annual average concentrations as undesirable outputs to construct an evaluation system for the synergistic governance environmental efficiency (SGEE) of PM_{2.5} and O₃ in Zhejiang Province (Table 2). The aim is to achieve economic development and improve the quality of PM_{2.5} and O₃ while decreasing the input of production factors per unit simultaneously. The above indicators are all sourced from the Zhejiang Statistical Yearbook and the Zhejiang Natural Resources and Environment Statistical Yearbook for the years 2015–2023, with individual missing data filled in by linear interpolation (Fang et al., 2023). To eliminate the deviation of economic indicators caused by the influence of inflation, the GDP value we have taken here has been

inflation-adjusted. The undesirable outputs are the annual average PM_{2.5} concentration values and annual average O₃ concentrations (the 90th percentile of the maximum 8-h average O₃ daily concentration in each city) expressed for each city (Ding et al., 2024).

The descriptive statistics for each variable are shown in Table 2.

2.3 Methods and models

2.3.1 Nemerov integrated pollution index

To comprehensively assess the pollution levels of PM_{2.5} and O₃ in different cities, the Nemerov integrated pollution (NIP) index method is introduced for evaluation (Ciarkowska and Gambus, 2020). This index is one of the most common-used methods for calculating comprehensive pollution indices both domestically and internationally. It particularly takes into account the factors with the most severe pollution and avoids the influence of subjective factors in the weighting process (Świdwa-Urbańska and Battle-Sales, 2021). The specific calculation formula (Equations 1, 2) is as follows:

$$P_i = C_i/S_i \tag{1}$$

$$NIP = \sqrt{\frac{(P_{i\max})^2 + (P_{i\text{ave}})^2}{2}} \tag{2}$$

In the formula: P_i is the single-factor pollution index of air pollutant i ; C_i is the measured concentration value of i ; S_i is the standard limit concentration value of air quality. According to the China Ambient Air Quality Standards (GB3095-2012), the secondary standard limits for PM_{2.5} and O₃ are 35 μg/m³ and 160 μg/m³ respectively. NIP is the Nemerov integrated pollution index, which means the higher the value, the greater the integrated pollution, the worse the synergistic management of PM_{2.5} and O₃; $P_{i\max}$ is the maximum value of the pollution index of air pollutant i ; $P_{i\text{ave}}$ is the arithmetic mean value of each air pollution index.

2.3.2 Undesirable output SBM-DEA model

2.3.2.1 SBM-DEA model

In this study, the Slacks-Based Measure (SBM)-Undesirable DEA model was employed to assess the SGEE of PM_{2.5} and O₃. The SBM model, constructed by Tone (2001), is a non-radial and non-angular DEA model. In the standard DEA model, radial requires that inputs or outputs move in the same proportion when evaluating efficiency, while oriented requires that modeling choices based on inputs (assuming outputs are constant) or outputs (assuming inputs are constant) be made when evaluating efficiency (Lu et al., 2019; Banker et al., 2004). The SBM model measures efficiency based on slack variables, overcomes the radial and oriented problems of classical DEA and facilitates the measurement of final results (Zhang et al., 2024; Lee, 2021; Deng et al., 2016).

Here, n cities ($n = 11$) are treated as n decision units, each of which contains three elements: inputs, desirable outputs, and undesirable outputs (PM_{2.5} and O₃ concentration). Then, input and desirable output variables are set as $X = (x_{ij}) \in R^{m \times n}$ and $Y = (y_{kj}) \in R^{s_1 \times n}$, non-desirable outputs as $Z = (z_{lj}) \in R^{s_2 \times n}$, and then make $X > 0$, $Y > 0$, and $Z > 0$. The production possibility set is $P = \{(x, y, z) | x \geq X\Lambda, y \leq Y\Lambda, z \geq Z\Lambda, \Lambda > 0\}$, where denotes the vector of weight coefficients $\Lambda = (\lambda_1, \lambda_2, \dots, \lambda_n) \in R^n$. The first

inequality in the set P denotes that the actual level of inputs is greater than the frontier level of inputs, and the second one denotes that the actual level of outputs is less than the frontier level of outputs. The SBM-DEA model with undesirable outputs is as follows (Fang et al., 2023):

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^x}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{k=1}^{s_1} \frac{s_k^y}{y_{k0}} + \sum_{l=1}^{s_2} \frac{s_l^z}{z_{l0}} \right)}$$

$$s.t. \begin{cases} x_{i0} = \sum_{j=1}^n \lambda_j x_j + s_i^x, \forall i; \\ y_{k0} = \sum_{j=1}^n \lambda_j y_j - s_k^y, \forall k; \\ z_{l0} = \sum_{j=1}^n \lambda_j z_j + s_l^z, \forall l; \\ s_i^x \geq 0; s_k^y \geq 0; s_l^z \geq 0; \lambda_j \geq 0; \forall i, j, k, l; \end{cases} \tag{3}$$

Among them, $s^x \in R^m$, $s^z \in R^{s_2}$, $s^y \in R^{s_1}$ respectively represent the surplus of inputs and undesirable outputs, as well as the shortage of desirable outputs. ρ is the SGEE of PM_{2.5} and O₃ in a city. m , s_1 and s_2 are the number of variables for inputs, desirable and undesirable outputs, respectively.

Equation 3 satisfies the assumption of constant returns to scale (CRS), and if constraints $\sum_{j=1}^n \lambda_j = 1$ are added to this equation, the assumption of variable returns to scale (VRS) is satisfied (Li et al., 2025; Fang et al., 2023).

When $\rho = 1$, that is, $s^x = 0$, and $s^y = s^z = 0$, it means that the SGEE of PM_{2.5} and O₃ in the evaluated city is effective. If $\rho < 1$, it means that the SGEE of PM_{2.5} and O₃ in the current city is non-effective and there are still improvements to be made (Fang et al., 2023).

2.3.2.2 Malmquist index based on SBM model

The Malmquist index is essentially the ratio of two distance function values and it is a theoretical index (Zheng, 2021). This research evaluates the Malmquist index using the Malmquist productivity index developed by Färe et al. (1992), which is based on input orientation and operates under the assumption of constant returns to scale (CRS):

$$M^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{E^t(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)} \cdot \frac{E^{t+1}(x^{t+1}, y^{t+1})}{E^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{4}$$

Where, $M^{t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ denotes total factor productivity (TFP) from period t to period $t + 1$. When TFP > 1, it indicates an increase in efficiency. While TFP < 1 indicates a decrease in efficiency. $E^{t+1}(x^t, y^t)$ denotes the value of SGEE of PM_{2.5} and O₃ management for a city in period t under the technology in period $t + 1$.

When $EC = \frac{E^{t+1}(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)}$, and $TC = \left[\frac{E^t(x^{t+1}, y^{t+1})}{E^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{E^t(x^t, y^t)}{E^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}}$ are set, the Malmquist index is then decomposed into efficiency change (EC) and technical change (TC, technological progress):

Färe et al. (1994), based on the decomposition method by Färe et al. (1992), derived different efficiency values using VRS and CRS. It further decomposed the efficiency change (EC) from Färe et al. (1992) decomposition method into pure technical efficiency change (PEC) and scale efficiency change (SEC).

$$M^{t+1} = EC*TC = PEC*SEC*TC \tag{5}$$

Among them, $PEC = \frac{E_v^{t+1}(x^{t+1}, y^{t+1})}{E_c^t(x^t, y^t)}$, and $SEC = \frac{E_c^{t+1}(x^{t+1}, y^{t+1})/E_v^{t+1}(x^{t+1}, y^{t+1})}{E_c^t(x^t, y^t)/E_v^t(x^t, y^t)}$. The subscript *c* represents CRS, while the subscript *v* represents VRS (Lu et al., 2019; Zofio, 2007).

2.3.3 Quantile regression model

To quantitatively study the influencing factors of AEE, and combined with existing relevant research (Lu et al., 2019; Ding et al., 2019), this study selected the following independent variables: education investment (EI, measured by fiscal education spending), scientific and technological innovation (STI, measured by R&D expenditure), industrial structure (IS, measured by the proportion of secondary industrial output value to GDP), and environmental regulation (ER, measured by the operating expenses of industrial waste gas treatment facilities in the current year, in ten thousand yuan). To reduce the deviation caused by different dimensions of explanatory variables, logarithmic processing was carried out to improve the interpretation accuracy of the model (Fang et al., 2023; Ding et al., 2024). Furthermore, based on the most common and fundamental estimation method in ordinary linear regression model—the Ordinary Least Squares (OLS) method—the following regression equation (Equation 6) has been constructed (Liu H. et al., 2022):

$$Y_{it} = \alpha_{it} + \beta_1 EI_{it} + \beta_2 STI_{it} + \beta_3 IS_{it} + \beta_4 ER_{it} + \varepsilon_{it} \tag{6}$$

In the above equation: *Y* represents the SGEE of PM_{2.5} and O₃; *i* denotes the 11 cities within the sample; *t* indicates the time variable (9 years); β₁–β₄ represents the impact coefficients of various factors on the SGEE of PM_{2.5} and O₃; α is the city fixed effect; and ε_{it} is the random error term, which follows the normal distribution assumption, and it represents the changed parts of the dependent variable that cannot be explained by the independent variables.

However, ordinary linear regression only obtain the expected value of the impact of various influencing factors on AEE and cannot analyze the effect of these factors on the distribution pattern of AEE (Wang, 2024). Quantile regression model (QRM) analysis more comprehensively describe the impact of independent variables on the changes in the dependent variable and its conditional distribution (Huang et al., 2017). It can profoundly reveal the marginal effects of influencing factors on AEE in different cities and delve into the quantile heterogeneity of these effects. When estimating parameters, the heterogeneity analysis of quantile methods uses the explained variable as a reference and specifies several different quantile points (Chou et al., 2020). It groups the sample points according to these quantile points and applies different weights to the sample points in different groups during estimation, thereby obtaining the estimated values. This method of exploring the quantile heterogeneity of influencing factors does not rely on reducing the sample size and takes into account the information from the entire sample, resulting in more robust outcomes (Veeravel et al., 2024; Ozkan et al., 2024).

Koenker and Hallock (2001) first proposed the theory of QRM, which involved a detailed study of significant quantiles in the distribution of *Y*|*X* to analyze and compare the effects of independent variables on the dependent variable at different quantile points. When the dependent variable is influenced differently by various portions of the independent variable

distribution, such as exhibiting left or right skewness, QRM capture the tail features of the distribution, providing a more comprehensive characterization of its properties. For a random variable *Y* in general, the linear conditional quantile function (Equation 7) for the τ-th quantile is given by Chou et al. (2020):

$$Q(\tau | X = x) = x'\hat{\beta}(\tau) \tag{7}$$

For any τ ∈ (0,1), where *x_i* is a *p*-dimensional vector, ρ_τ(·) is the tilted absolute value function, and the estimate β̂(τ) shown in Equation 8 is referred to as the regression coefficient estimate at the τ-th quantile.

$$\hat{\beta}(\tau) = \underset{\beta \in R^p}{\operatorname{arg\,min}} \sum_{i=1}^n \rho_{\tau}(y_i - x_i'\beta) \tag{8}$$

Finally, this study takes static SGEE of PM_{2.5} and O₃ as the dependent variable and uses a QRM to reveal the key influencing factors at different levels of static SGEE of PM_{2.5} and O₃. The calculation formula (Equation 9) is as follows:

$$Y_{it,q} = \alpha_{it,q} + \beta_{1,q} \ln EI_{it,q} + \beta_{2,q} \ln STI_{it,q} + \beta_{3,q} \ln IS_{it,q} + \beta_{4,q} \ln ER_{it,q} + \varepsilon_{it,q} \tag{9}$$

In the above formula: *q* represents the selected quantiles, which are 10%, 25%, 50%, 75%, and 90%; β_{1,q}–β_{4,q} indicates the impact effect of various factors on the SGEE of PM_{2.5} and O₃ at different level quantiles (Wang, 2024). *i* denotes the 11 cities within the sample; *t* indicates the time variable (9 years); ε_{it,q} is the random error term, which follows the normal distribution assumption.

3 Results

3.1 Overall pollution characteristics of PM_{2.5} and O₃

3.1.1 Spatial-temporal distribution of PM_{2.5} and O₃ concentrations

Based on Arcgis 10.0 software, the spatial-temporal distribution characteristics of PM_{2.5} and O₃ concentrations in 11 cities of Zhejiang Province are revealed. For comparison, the distribution status of pollutant concentrations in four cross-sectional time periods from 2014–2017–2020–2022 are selected for specific analysis. The results are shown in Figures 1, 2.

Comparing Figures 1, 2, it can be found that, (1) there were significant time-series variation differences in PM_{2.5} and O₃ concentrations in 11 cities in Zhejiang Province, with PM_{2.5} generally more polluted before 2017 and O₃ generally more severe after 2017. In particular, PM_{2.5} concentrations showed a steady improvement trend, while O₃ concentrations showed multiple fluctuations, with pollution first increasing, then decreasing and improving, and finally rebounding and worsening. It has been shown that O₃ is the primary pollutant in the air environment of Zhejiang Province in recent years (Ding et al., 2024), especially in the summer when the temperature is high. (2) There were some spatial distribution differences of PM_{2.5} and O₃ concentrations in 11 cities in Zhejiang Province. In terms of the average PM_{2.5} concentration in the past years, Hangzhou >

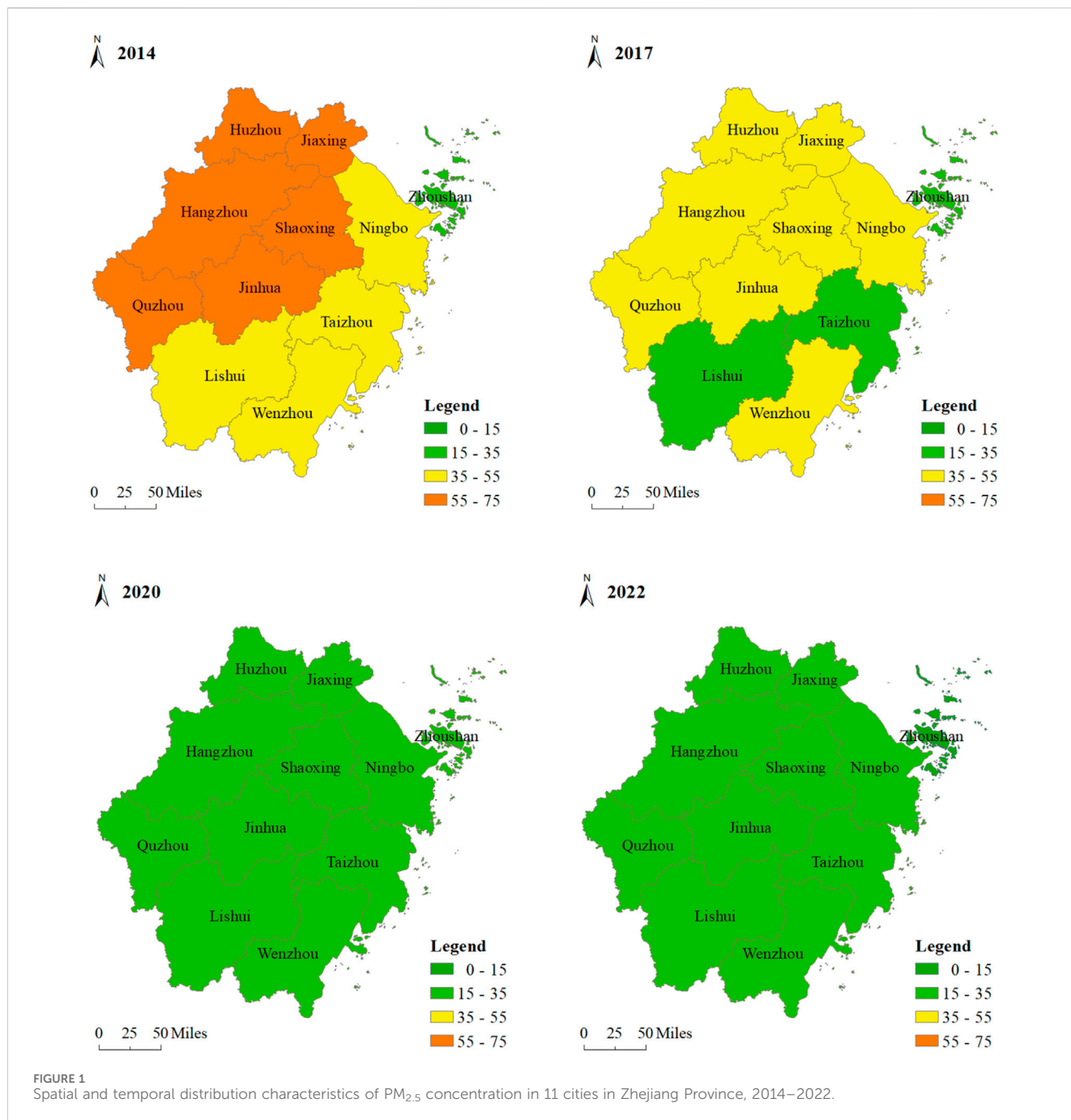


FIGURE 1 Spatial and temporal distribution characteristics of PM_{2.5} concentration in 11 cities in Zhejiang Province, 2014–2022.

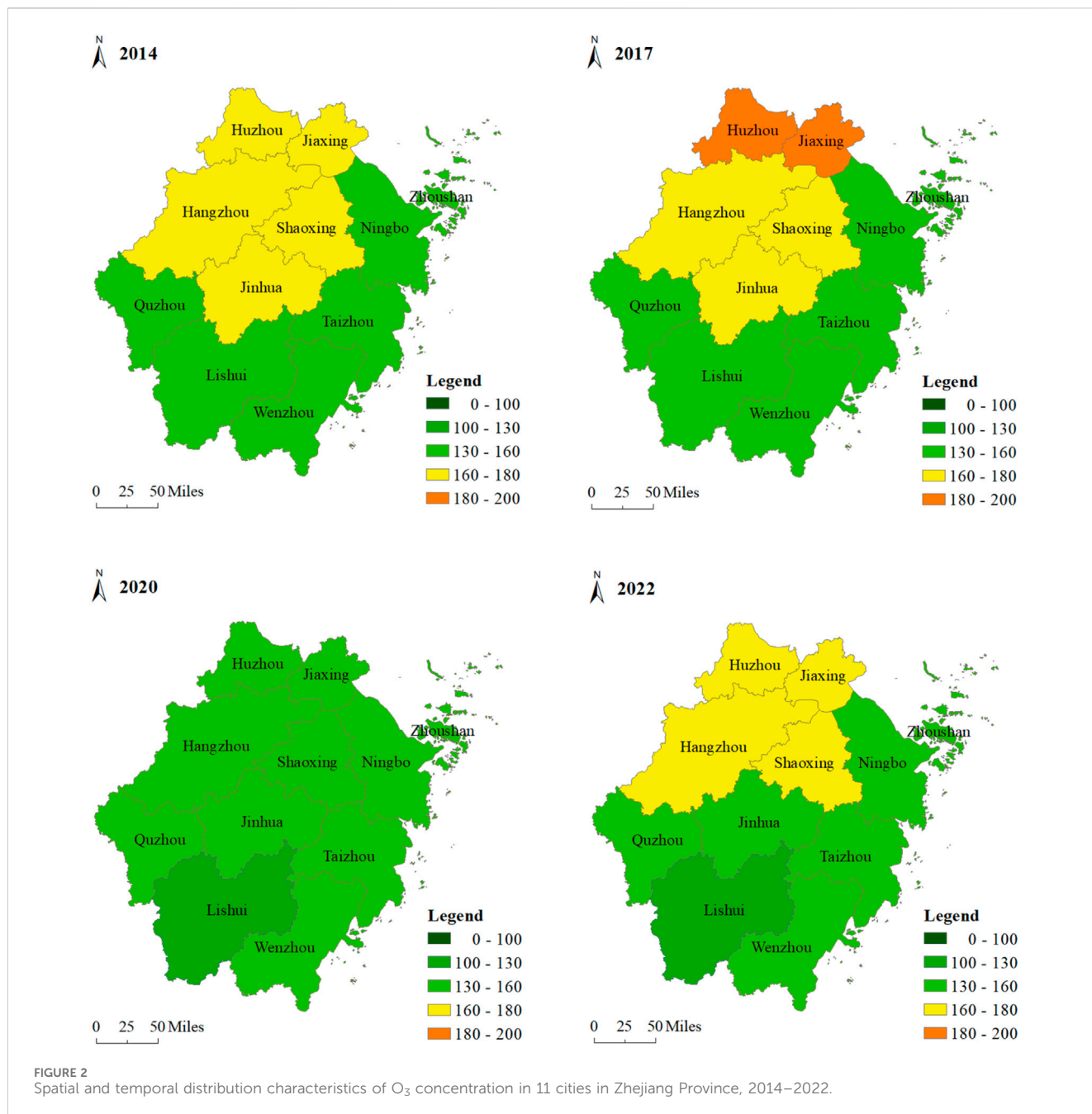
Shaoxing > Huzhou > Jinhua > Jiaying > Quzhou > Wenzhou > Ningbo > Taizhou > Lishui > Zhoushan. Sorting from the average O₃ concentration in the past years, Huzhou > Jiaying > Hangzhou > Shaoxing > Jinhua > Ningbo > Quzhou > Taizhou > Wenzhou > Zhoushan > Lishui. Cities with more severe pollution of both are mainly located in the cities around Hangzhou Bay in the north-central part of Zhejiang, such as Huzhou, Jiaying, Hangzhou and Shaoxing, which are also the key cities in the Yangtze River Delta region for the prevention and control of air pollution. Cities with relatively mild pollution levels are mainly located in Zhoushan and Lishui, characterized by relatively backward industrial output, minimal anthropogenic pollution emissions, and favorable natural conditions. (3) Generally, Zhejiang Province has not yet

achieved significant synergistic management of PM_{2.5} and O₃. In the future, how to efficiently promote the stable reduction of PM_{2.5} and O₃ remains a tough task (Shu et al., 2024).

3.1.2 Comprehensive evaluation of PM_{2.5} and O₃ pollution

Based on the above mentioned NIP index calculation, an evaluation of the comprehensive status of PM_{2.5} and O₃ pollution in 11 cities of Zhejiang Province was conducted, with the results shown in Figure 3.

From the above Figure 3, it can be seen that (1) the NIP values in various cities showed a significant downward trend, indicating that the comprehensive pollution status of PM_{2.5} and O₃ in these cities has



improved to some extent. Among them, the cities with relatively lighter comprehensive pollution are mainly coastal cities such as Zhoushan, Ningbo, and Wenzhou. (2) The NIP values of various cities exhibited certain regional disparities. Based on the average NIP values over the years, the ranking is as follows: Huzhou > Hangzhou > Jiaxing > Shaoxing > Jinhua > Quzhou > Ningbo > Wenzhou > Taizhou > Lishui > Zhoushan. Cities in northern and central Zhejiang have significantly higher NIP values compared to those in the southeastern part. The former has a relatively higher concentration of air pollution-intensive industries (Ding and Fang, 2022), and their meteorological and topographical conditions are less favorable for pollutant dispersion compared to the coastal cities in the southeast. (3) In 2022, the NIP values of various cities showed a certain rebound, indicating that there were considerable challenges in the coordinated

management of PM_{2.5} and O₃. In particular, affected by adverse meteorological conditions and precursor pollution emissions, it is necessary to actively prevent the rebound of PM_{2.5} and O₃ pollution concentrations (Wang L. et al., 2025).

3.2 Estimation results of SGEE of PM_{2.5} and O₃

3.2.1 Analysis of static SGEE of PM_{2.5} and O₃

Through the non-radial measurement SBM-DEA model, the SGEE of PM_{2.5} and O₃ in 11 prefecture-level cities in Zhejiang Province was estimated based on the aforementioned Equation 3, and the results are shown in Table 3.

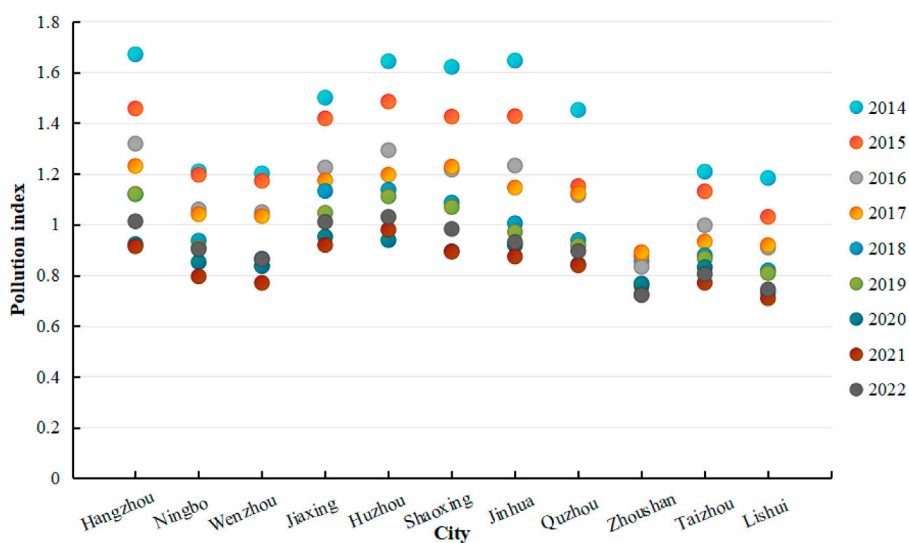


FIGURE 3 Analysis of NIP index of PM_{2.5} and O₃ pollution in Zhejiang Province from 2014 to 2022.

TABLE 3 The static estimation results of SGEE of PM_{2.5} and O₃ in 11 cities in Zhejiang Province from 2014 to 2022.

Area	City	2014	2017	2020	2022	Average for 9 years	Rank
Hangzhou Bay urban agglomeration	Hangzhou	0.412	0.633	0.707	0.671	0.606	3
	Ningbo	0.625	0.761	0.802	0.744	0.733	2
	Jiaxing	0.360	0.384	0.364	0.344	0.363	11
	Huzhou	0.406	0.423	0.325	0.301	0.364	10
	Shaoxing	0.412	0.424	0.463	0.442	0.435	8
	Zhoushan	1.000	0.913	1.000	1.000	0.978	1
Non-Hangzhou Bay area	Wenzhou	0.403	0.448	0.451	0.475	0.444	7
	Jinhua	0.399	0.502	0.508	0.512	0.480	5
	Quzhou	0.401	0.428	0.418	0.407	0.413	9
	Taizhou	0.461	0.467	0.506	0.473	0.477	6
	Lishui	0.590	0.617	0.491	0.567	0.566	4
Overall average		0.497	0.545	0.549	0.540	0.533	

From the above Table 3, it can be seen that during the 9 years, the average value of the overall SGEE of PM_{2.5} and O₃ of the 11 cities in Zhejiang Province was 0.533, which was still about 46.7% of the improvement margin from the production frontier (the maximum output level that can be achieved with a given input), and a large potential for PM_{2.5} and O₃ environmental improvement existed.

In terms of SGEE of PM_{2.5} and O₃ in each city, the static efficiency values showed a fluctuating increasing trend. Among them, only Zhoushan City achieved the production frontier in 7 years, while the remaining 10 cities have not reached the synergistic emission reduction technology level of PM_{2.5} and O₃ compared to the leading cities. It implies that the vast majority still have significant potential for improving SGEE of PM_{2.5} and O₃,

indicating regional differences in SGEE of PM_{2.5} and O₃ among different cities. From the average environmental efficiency values of the 9-year period in each city, the ranking is as follows: Zhoushan > Ningbo > Hangzhou > Lishui > Jinhua > Taizhou > Wenzhou > Shaoxing > Quzhou > Huzhou > Jiaxing. The ranking indicates similarities with the city ranking based on PM_{2.5} environmental efficiency in previous study (Fang et al., 2023).

Over different years, the ranking of SGEE of PM_{2.5} and O₃ have varied across different cities. The cities with higher SGEE of PM_{2.5} and O₃ are mainly Zhoushan, Ningbo, and Hangzhou, which are important regions leading the development of science and technology and emerging industries in Zhejiang Province. Since the 13th Five-Year Plan, relying on huge investment in education

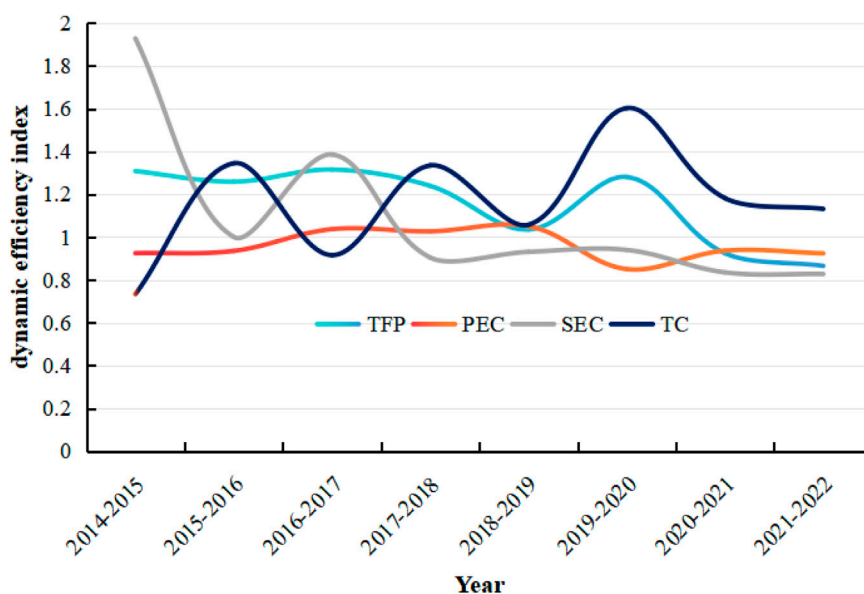


FIGURE 4 Changes in total factor productivity and decomposition indicators of dynamic SGEE of PM_{2.5} and O₃ in Zhejiang Province.

and technological innovation, especially the role of new research and development institutions in the process of enterprises' green transformation, Ningbo and Hangzhou have strengthened the digital management transformation and end-of-pipe control of key polluting industries (Lu et al., 2019; Ding and Fang, 2022; Ding et al., 2024), effectively reducing emissions of atmospheric pollutants such as NO_x and particulate matter. It has accelerated the treatment of volatile organic compounds (VOCs) and improved the SGEE of PM_{2.5} and O₃. As an international island tourism city, Zhoushan has its unique characteristics of being green and low-pollution in terms of industrial policy positioning. In recent years, around technological innovations such as green new materials and digital marine industries, Zhoushan has continued to perform significantly in the control of air pollution sources, thus having the highest SGEE value. Cities with low SGEE of PM_{2.5} and O₃ include Jiaxing, Huzhou, Quzhou, and Shaoxing. It means that in the future, the area around Hangzhou Bay will continue to be a key region for the coordinated control of PM_{2.5} and O₃ in Zhejiang Province, including preventing the rebound of PM_{2.5} and O₃ concentrations (Wang H. et al., 2025).

3.2.2 Analysis of dynamic SGEE of PM_{2.5} and O₃

To further clarify the dynamic evolution process of the SGEE of PM_{2.5} and O₃ in various cities in Zhejiang Province, a non-radial DEA model with the Malmquist index (Zofio, 2007) was employed. Based on Equations 4, 5, the total factor productivity (TFP) of each city was measured (Lu et al., 2019; Ding et al., 2019), decomposed into three components: pure technical efficiency change (PEC), scale efficiency change (SEC), and technological progress index (TC), as shown in Figure 4.

From a provincial perspective, the average TFP of the SGEE of PM_{2.5} and O₃ in Zhejiang Province from 2014 to 2022 was 1.153, indicating an annual average growth of 15.3% in the overall SGEE of PM_{2.5} and O₃. It suggests a clear improvement trend in the

relationship between atmospheric PM_{2.5} and O₃ coordinated control and regional economic development in Zhejiang Province.

From the results of the index decomposition, the average value of the PEC is 0.961 and shows a slightly decreasing trend in general, which means that the PEC is an important factor inhibiting the improvement of environmental productivity in the synergistic management of PM_{2.5} and O₃ in Zhejiang Province.

The average value of SEC is 1.094 and shows a decreasing trend, which implies that enterprise scale expansion contributes to the increase of economic efficiency. Relying on the current digital transformation of enterprises and the development of digital economy in Zhejiang Province, SEC helps to improve the efficiency of optimal allocation of resources, reduce energy consumption and pollution emissions in dimensions such as product management and transportation (Ding et al., 2019; Fang et al., 2023), and promote synergistic emission reduction of PM_{2.5} and VOCs, but the effect of this role is gradually weakening.

The average value of the TC is 1.163, fluctuating up and down around 1 and tending to be stable and greater than 1, with an overall average annual growth rate of 16.3%, which is higher than the average annual growth rate of the index of SCE of 9.4%.

The above indicates that technological progress represented by process innovation, equipment improvement, and upgrading of pollution control technologies is the main driving force for improving the SGEE of PM_{2.5} and O₃ (with Hangzhou and Ningbo as typical examples). However, the contribution of pure technical efficiency characterized by soft technical conditions such as innovative management modes and optimized industrial structures has not yet been realized. Therefore, actively and effectively optimizing industrial structures (such as reducing the proportion of industries with high VOCs emissions), innovating enterprise management modes, optimizing resource allocation, and focusing on enhancing technological efficiency are key pathways for future improvements in SGEE of PM_{2.5} and O₃ in Zhejiang.

TABLE 4 OLS regression results of static SGEE of PM_{2.5} and O₃ in Zhejiang Province.

Variable	M1	M2	M3
(Constant)	0.575 *** (4.243)	2.482 *** (5.289)	2.647 *** (5.133)
Ln EI	0.025 (0.700)	-0.041 (-1.136)	-0.060 (-1.374)
Ln STI	-0.196 *** (-2.655)	-0.013 (-0.165)	-0.017 (-0.213)
Ln IS		-0.478*** (-4.216)	-0.512*** (-4.207)
Ln RE			0.021 (0.779)
R ²	0.090	0.233	0.238
Samples	99	99	99

Note: The numbers in parentheses indicate the standard error t-values, *p < 0.1, **p < 0.05, ***p < 0.01.

3.3 Factors influencing the SGEE of PM_{2.5} and O₃

3.3.1 Estimation of OLS regression model

Due to the potential correlations or multi-collinearity among the aforementioned influencing factors, this study first conducted a correlation coefficient test and Variance Inflation Factor test on the four variables mentioned above (Dormann et al., 2013). The test results indicated that the average VIF was 9.87 (<10), suggesting that there was no serious multi-collinearity, allowing all explanatory variables to be included in the regression model.

Then, employing OLS regression, the study analyzed the SGEE of PM_{2.5} and O₃ along with four independent variables for 11 cities from 2004 to 2022. The results indicate that the model passed the diagnostic tests. The effects of EI and STI on the SGEE of PM_{2.5} and O₃ are estimated by step-based regression (see Table 4 for details). It can be found that in the initial OLS model (M1), LnEI coefficient is positive but does not pass the significance test, and LnSTI has a significant negative impact. With the introduction of intermediary variables (M2 and M3), there is a significant negative correlation between the influence of LnIS on the SGEE of PM_{2.5} and O₃, while other variables fail the significance test. At the same time, in the three OLS models, the goodness of fit are low, and the OLS model estimation results are generally not ideal.

3.3.2 Estimation of the QRM

Since the low goodness of fit of the OLS regression model, accurate influence judgments cannot be made based solely on the obtained regression coefficients (Cade and Noon, 2003; Wang, 2024). Therefore, it is necessary to further analyze the influence coefficient using a QRM. The results are presented in Table 5 and Figure 5.

Based on the regression results, the influence coefficients of different factors show significant variation across different quantiles, specifically reflected in the following aspects:

- (1) Educational investment: it shows a non-significant positive correlation before the 0.1 quantile, but a significant negative correlation after the 0.25 quantile (Figure 5a). It indicates that in regions with low SGEE of PM_{2.5} and O₃, an increase in the level of educational investment promotes the improvement of environmental efficiency. Conversely, in regions with high SGEE of PM_{2.5} and O₃, an increase in educational investment

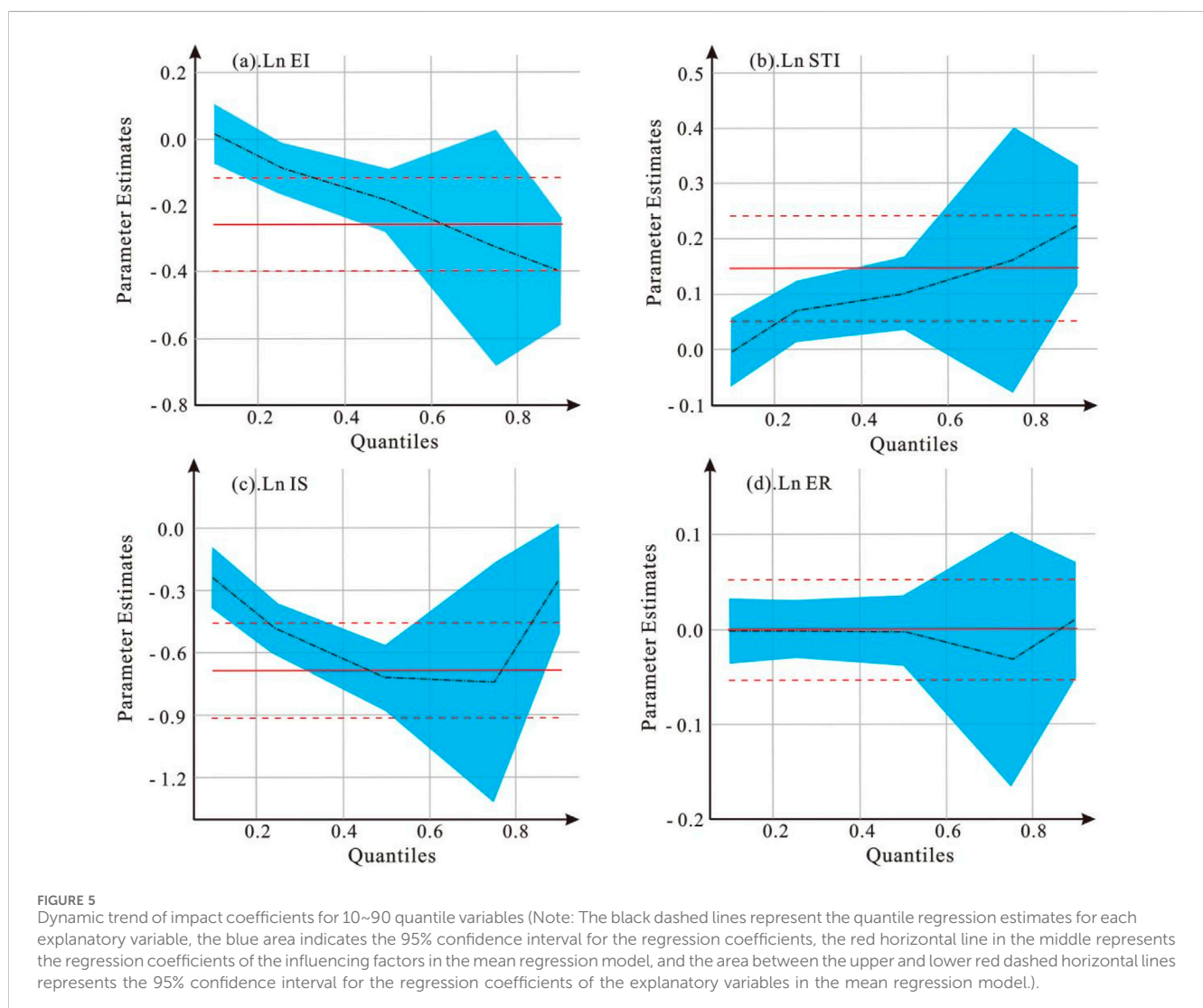
suppresses the improvement of environmental efficiency. Existing research has shown that green education helps to consolidate the achievements of ecological civilization construction and improve the level of environmental governance (Liu K. et al., 2022; Cheng et al., 2024). An increase in educational investment could, in the short term, mobilize students and stimulate public participation in environmental protection, gradually assisting to raise ecological conservation awareness throughout society. It, in turn, strengthens public supervision of environmental pollution and enhances the efficiency of environmental governance (Varela-Candamio et al., 2018). Therefore, in regions with SGEE of PM_{2.5} and O₃ for medium to low levels (such as Jiaying and Shaoxing), an increase in educational investment is beneficial for managing key air pollutants. However, in high environmental efficiency areas like Zhoushan and Ningbo, increased educational investment lead to a resource “Crowding-out effect” on the inputs for managing air pollutants (Tao et al., 2022; Underdal, 2010). Given limited financial resources, an increase in educational investment can undermine the stable operation of facilities for managing industrial emissions, thereby reducing the SGEE of PM_{2.5} and O₃. Moreover, an increase in educational investment enhances the overall human capital of the province, thereby accelerating economic growth, but it does not directly lead to an improvement in environmental quality.

- (2) Technological innovation: After the 0.25 quantile point, there is a significant positive correlation, and the regression coefficient increases to some extent (Figure 5b). It indicates that the rise in the level of technological innovation can effectively promote the improvement of the SGEE of PM_{2.5} and O₃, and the enhancing effect is more pronounced in areas with higher SGEE of PM_{2.5} and O₃. Existing research indicates that through technological breakthroughs and innovation, it is possible to gradually elucidate the mechanisms of PM_{2.5} and O₃ formation, develop catalytic technologies and equipment to eliminate pollutant concentrations, and establish a comprehensive and multi-dimensional monitoring system for ozone and its precursors (Cui et al., 2023; Chen et al., 2019). It can effectively organize and implement collaborative prevention and control plans and strategies for PM_{2.5} and O₃ pollution, thereby improving the

TABLE 5 Quantile regression estimation of the static SGEE of PM_{2.5} and O₃ in Zhejiang Province.

Variable	Q10	Q25	Q50	Q75	Q90
(Constant)	1.228 (0.323)	2.319*** (0.285)	3.520*** (0.348)	4.155** (1.282)	2.516*** (0.574)
Ln EI	0.016 (0.452)	-0.087** (0.395)	-0.185*** (0.487)	-0.327* (0.487)	-0.399*** (0.080)
Ln STI	-0.004 (0.031)	0.070** (0.027)	0.102** (0.033)	0.162* (0.121)	0.225*** (0.054)
Ln IS	-0.239** (0.074)	-0.490** (0.064)	-0.719** (0.079)	-0.739** (0.291)	-0.240* (0.130)
Ln RE	-0.002 (0.017)	0.001 (0.015)	-0.001 (0.018)	-0.032 (0.067)	0.011 (0.030)
Samples	99	99	99	99	99

Note: The quantiles selected are 10th, 25th, 50th, 75th and 90th, where the 10th and 25th percentiles represent low SGEE, of PM_{2.5} and O₃, and the 75th and 90th percentiles represent high SGEE, of PM_{2.5} and O₃; the numbers in parentheses indicate the standard error t-values, *p < 0.1, **p < 0.05, ***p < 0.01.



SGEE of PM_{2.5} and O₃. Meanwhile, cities like Hangzhou and Ningbo, which have advanced modern technological means, have constructed a digitized and intelligent air governance system that achieves precise identification of pollution sources, real-time aggregation of PM_{2.5} and O₃ monitoring

data, and early prediction and warning processing, thereby enabling SGEE of PM_{2.5} and O₃.

(3) Industry structure: a significant negative correlation is observed at all quantile points. It illustrates that a decrease in the proportion of industrial output value effectively

enhances the SGEE of $PM_{2.5}$ and O_3 (Figure 5c). From the perspective of the impact coefficients, in cities with low and high SGEE of $PM_{2.5}$ and O_3 , the suppressive effect of industrial structure adjustment on environmental efficiency is somewhat reduced. Thus, the improvement of SGEE of $PM_{2.5}$ and O_3 through industrial structure adjustment is mainly reflected in cities at the 0.25–0.75 quantile points, while its impact on high-efficiency cities is limited. Existing research demonstrates that industrial sources are the primary contributors to $PM_{2.5}$ and O_3 pollution (Li et al., 2024; Yang J. et al., 2025). With the adjustment of the industrial structure, the reduction and elimination of industries related to severe air pollution, along with Zhejiang Province's acceleration of the green transformation and upgrading of traditional industries (Ding et al., 2020), and the vigorous promotion of the development of high-tech industries and strategic emerging industries, will help enhance the SGEE of $PM_{2.5}$ and O_3 . It is particularly evident in cities such as Hangzhou, Ningbo, and Wenzhou. For instance, Hangzhou and Ningbo are promoting industrial digitalization and the digitalization of industries, utilizing digital technologies to advance smart manufacturing. It enhances operational efficiency in enterprises, drives technological iteration, and focuses on air pollution reduction and control in key industries. The aim is to address the prominent issues causing $PM_{2.5}$ and O_3 pollution.

- (4) Environmental regulation: there is no significant correlation at any quantile (Figure 5d), which indicates that the current investment and intensity of air pollution environmental regulation have not had a significant impact on the SGEE of $PM_{2.5}$ and O_3 . On one hand, the current operational funding for air pollution control under environmental regulation mainly focuses on the management of industrial pollutants such as SO_2 and NO_x , and has not had a direct and effective impact on the collaborative governance of $PM_{2.5}$ and O_3 pollution. On the other hand, a significant portion of the pollution sources for urban $PM_{2.5}$ and O_3 comes from traffic and mobile sources, which are not directly reflected in the investments in environmental regulation. Therefore, environmental regulations need to raise the emission standards for environmental pollutants and strengthen the supervision and control of pollutant emissions (Fang et al., 2023). Meanwhile, while continuing to address industrial pollution sources, there should be increased efforts for the collaborative governance of pollution from traffic and mobile sources (Jiang et al., 2019). For instance, cities can reduce the impact of motor vehicle emissions of $PM_{2.5}$ and O_3 by promoting clean energy vehicles, strengthening vehicle exhaust emission standards, and facilitating the development of public transportation.

3.4 Discussion and policy implications

Based on the above analysis, the following strategies and recommendations for the synergistic governance of $PM_{2.5}$ and O_3 are proposed:

- (1) Rationally value the limited role of educational investment in enhancing the SGEE of $PM_{2.5}$ and O_3 . In existing research, educational investment has been an overlooked variable influencing AEE (Lu et al., 2019; Fang et al., 2023). The study indicates that educational investment primarily affects the enhancement of SGEE of $PM_{2.5}$ and O_3 during the medium to low efficiency stages. It suggests that in terms of the areas severely affected by $PM_{2.5}$ and O_3 pollution and with relatively low SGEE of $PM_{2.5}$ and O_3 , increasing educational investment and public awareness could mobilize public recognition of $PM_{2.5}$ and O_3 pollution in the short term, leading to the adoption of proactive and effective measures to improve pollution management efficiency. However, in regions with higher SGEE of $PM_{2.5}$ and O_3 , an increase in educational investment may lead to a “Crowding-out effect” on resources allocated for $PM_{2.5}$ and O_3 synergistic governance, necessitating the use of other regulatory measures for deeper efficiency enhancements (Tao et al., 2022; Underdal, 2010).
- (2) Strengthen the role of technological innovation in improving the SGEE of $PM_{2.5}$ and O_3 . Existing research has shown that technological advancement is a key factor in enhancing AEE. Therefore, cities in Zhejiang should increase investment in technological research and development, cultivate high-level scientific and technological talent, implement innovation-driven development strategies, and strengthen independent innovation capabilities (Hua et al., 2022). It is essential to enhance the cooperation and connection among local research institutions, enterprises, and environmental protection departments, and to establish various forms of technology innovation alliances to improve the technologies and capabilities for the synergistic governance of $PM_{2.5}$ and O_3 . Cities like Hangzhou and Ningbo should continue to elevate the level of technological innovation applications, with a focus on enterprises that are highly polluting, difficult to manage, and have significant pollution outputs. Additionally, they should promote the extensive application of cutting-edge fields such as *Internet+* and big data to enhance the applicability of technological innovations and improve the level of comprehensive governance technologies (Jiang et al., 2019; Ding et al., 2020).
- (3) Continuous optimization of industrial structure to promote the improvement of SGEE of $PM_{2.5}$ and O_3 . Existing research has shown that adjusting the industrial structure is an important factor in enhancing AEE (Fang et al., 2023). Currently, Zhejiang should continue to eliminate high energy consumption, high pollution, and high emissions industries, reduce the proportion of heavy-polluting industrial output, and accelerate the green transformation and development of traditional industries (Wang et al., 2023; Ding and Fang, 2022). Among them, Hangzhou and Ningbo should fully leverage the advantages of the service sector and strategic emerging industries, and continue to capitalize on the advantages of the digital economy to accelerate the technological upgrading of the manufacturing sector and vigorously develop high-tech industries (Zhang et al., 2023). Meanwhile, cities like Jiaying and Shaoxing should

focus on improving their own environmental protection industries while enhancing the processes of industrial products, reducing high-energy-consuming enterprises, and promoting industrial transformation and upgrading.

4 Conclusion

A scientific evaluation of atmospheric environmental efficiency is an important measure for continuously improving regional air quality. The study focuses on the synergistic governance environmental efficiency of PM_{2.5} and O₃, using 11 cities in Zhejiang Province, a typical green transformation area in eastern China, as a case study for empirical analysis. The results show that:

- (1) The PM_{2.5} and O₃ concentrations in the 11 cities of Zhejiang Province show significant spatio-temporal variation. Cities experiencing severe levels of both types of pollution are primarily found in the central and northern parts of Zhejiang, especially in the Hangzhou Bay area, including Huzhou, Jiaxing, Hangzhou, and Shaoxing, which also exhibit higher NIP values. There remain challenges in the simultaneous governance and emission reduction of PM_{2.5} and O₃.
- (2) The average SGEE of PM_{2.5} and O₃ in Zhejiang Province is 0.533, indicating there is approximately 46.7% room for improvement compared to the production frontier. Cities with higher environmental efficiency mainly include Zhoushan, Ningbo, and Hangzhou. Technological advancement is the main driving force behind the improvement of SGEE of PM_{2.5} and O₃, while the contribution of pure technical efficiency needs further exploration.
- (3) The results of the quantile regression indicate that the influence coefficients of different factors on the synergistic governance environmental efficiency of PM_{2.5} and O₃ vary significantly at different quantiles. Educational investment primarily improves the SGEE of PM_{2.5} and O₃ during low-efficiency stages, while it exerts a certain “Crowding-out effect” on resources during high-efficiency stages. In contrast, the rise in technological innovation levels and the adjustment of industrial structures can effectively promote the improvement of SGEE of PM_{2.5} and O₃.

Although the study has explored the SGEE of PM_{2.5} and O₃ to some extent, there are limitations due to the restricted range of sample cities and indicator data. Future studies could focus on other emerging pollutants, such as VOCs, to continuously optimize the indicator system for undesirable outputs of AEE. Additionally, it will be necessary to expand the sample size of cities over a broader range, to assess the impact and incentives of indicators such as educational investment, technological innovation, and the digital economy on AEE at a larger scale (e.g., at the inter-city or national level) and in a more precise manner.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

Author contributions

BJ: Conceptualization, Data curation, Investigation, Resources, Writing – original draft. QZ: Data curation, Investigation, Writing – original draft. LL: Formal Analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft. LD: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review and editing.

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Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenvs.2025.1632050/full#supplementary-material>

References

- Banker, R. D., Cooper, W. W., Seiford, L. M., Thrall, R. M., and Zhu, J. (2004). Returns to scale in different DEA models. *Eur. J. Operational Res.* 154 (2), 345–362. doi:10.1016/s0377-2217(03)00174-7
- Cade, B. S., and Noon, B. R. (2003). A gentle introduction to quantile regression for ecologists. *Front. Ecol. Environ.* 1 (8), 412–420. doi:10.1890/1540-9295(2003)001[0412:agitrq]2.0.co;2
- Chen, J., Wang, S., Zhou, C., and Li, M. (2019). Does the path of technological progress matter in mitigating China's PM_{2.5} concentrations? Evidence from three urban agglomerations in China. *Environ. Pollut.* 254, 113012. doi:10.1016/j.envpol.2019.113012
- Cheng, Y., Zhao, G., Meng, W., and Wang, Q. (2024). Resources utilization, taxation and green education: a path to sustainable power generation. *Resour. Policy* 88, 104389. doi:10.1016/j.resourpol.2023.104389
- Chou, L. C., Zhang, W. H., Wang, M. Y., and Yang, F. M. (2020). The influence of democracy on emissions and energy efficiency in America: new evidence from quantile regression analysis. *Energy Environ.* 31 (8), 1318–1334. doi:10.1177/0958305x19882382
- Ciarkowska, K., and Gambus, F. (2020). Building a quality index for soils impacted by proximity to an industrial complex using statistical and data-mining methods. *Sci. Total Environ.* 740, 140161. doi:10.1016/j.scitotenv.2020.140161
- Cui, Y., Zhong, C., Cao, J., and Guo, M. (2023). Can green finance effectively mitigate PM_{2.5} pollution? What role will green technological innovation play? *Energy Environ.*, doi:10.1177/0958305x231204030
- Deng, G., Li, L., and Song, Y. (2016). Provincial water use efficiency measurement and factor analysis in China: based on SBM-DEA model. *Ecol. Indic.* 69, 12–18. doi:10.1016/j.ecolind.2016.03.052
- Ding, L., Chen, K., Hua, Y., Dong, H., and Wu, A. (2020). Investigating the relationship between the industrial structure and atmospheric environment by an integrated system: a case study of Zhejiang, China. *Sustainability* 12 (3), 1278. doi:10.3390/su12031278
- Ding, L., and Fang, X. (2022). Spatial-temporal distribution of air-pollution-intensive industries and its social-economic driving mechanism in Zhejiang Province, China: a framework of spatial econometric analysis. *Environ. Dev. Sustain.* 24 (2), 1681–1712. doi:10.1007/s10668-021-01503-z
- Ding, L., Lu, Y. Y., and Ye, S. S. (2019). Evaluation of atmospheric environment efficiency and regional differences in Zhejiang. *J. Saf. Environ.* 19 (3), 1075–1085.
- Ding, L., Wang, L., Fang, X., Diao, B., Xia, H., Zhang, Q., et al. (2024). Exploring the spatial effects and influencing mechanism of ozone concentration in the Yangtze River Delta urban agglomerations of China. *Environ. Monit. Assess.* 196 (7), 603. doi:10.1007/s10661-024-12762-4
- Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., et al. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography* 36 (1), 27–46. doi:10.1111/j.1600-0587.2012.07348.x
- Fang, X., Gao, B., Cui, S., Ding, L., Wang, L., and Shen, Y. (2023). Regional differences in PM_{2.5} environmental efficiency and its driving mechanism in Zhejiang Province, China. *Atmosphere* 14 (4), 672. doi:10.3390/atmos14040672
- Färe, R., Grosskopf, S., Lindgren, B., and Roos, P. (1992). Productivity changes in Swedish pharmacies 1980–1989: a non-parametric malmquist approach. *J. Prod. Analysis* 3 (1), 85–101. doi:10.1007/bf00158770
- Färe, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *Am. Econ. Rev.*, 66–83. Available online at: <https://www.jstor.org/stable/2117971>.
- Fu, Y. X., Xie, H. J., Zhan, J. J., and Zhang, X. (2024). Research on atmospheric environmental efficiency in China based on dynamic NSBM model. *J. Syst. Sci. Math. Sci.*, 1–20. doi:10.12341/jssms240135
- Guo, J., Wu, X. H., and Chen, Y. F. (2020). Construction and demonstration of two-stage DEA model for estimation of haze emission efficiency. *China Soft Sci. Mag.* 10, 184–192.
- He, Q., Han, J., Guan, D., Mi, Z., Zhao, H., and Zhang, Q. (2018). The comprehensive environmental efficiency of socioeconomic sectors in China: an analysis based on a non-separable bad output SBM. *J. Clean. Prod.* 176, 1091–1110. doi:10.1016/j.jclepro.2017.11.220
- Hua, Y. D., Hu, K. M., Qiu, L. Y., Dong, H. A., Ding, L., and Lo, S. L. (2022). Exploring the interaction relationship between beautiful China-SciTech innovation using coupling coordination and predictive analysis: a case study of Zhejiang. *Environ. Dev. Sustain.* 24, 12097–12130. doi:10.1007/s10668-021-01936-6
- Huang, Q., Zhang, H., Chen, J., and He, M. (2017). Quantile regression models and their applications: a review. *J. Biometrics Biostat.* 8 (3), 1–6. doi:10.4172/2155-6180.1000354
- Huang, X., Liu, M., Chen, R., Gao, S., Xie, Q., and Feng, Q. (2021). Evaluation and spatiotemporal characteristics of atmospheric environment efficiency in Shandong province based on super-SBM model. *Environ. Res. Commun.* 3 (11), 115002. doi:10.1088/2515-7620/ac3409
- Jiang, B., Ding, L., and Fang, X. (2019). Sustainable development of new urbanization from the perspective of coordination: a new complex system of urbanization-technology innovation and the atmospheric environment. *Atmosphere* 10 (11), 652. doi:10.3390/atmos10110652
- Koenker, R., and Hallock, K. F. (2001). Quantile regression. *J. Econ. Perspect.* 15 (4), 143–156. doi:10.1257/jep.15.4.143
- Kong, L., Song, M., Li, X., Liu, Y., Lu, S., Zeng, L., et al. (2024). Analysis of China's PM_{2.5} and ozone coordinated control strategy based on the observation data from 2015 to 2020. *J. Environ. Sci.* 138, 385–394. doi:10.1016/j.jes.2023.03.030
- Lee, H. S. (2021). An integrated model for SBM and Super-SBM DEA models. *J. Operational Res. Soc.* 72 (5), 1174–1182. doi:10.1080/01605682.2020.1755900
- Li, L., He, M., Liang, X., Deng, H., and Yang, R. (2024). How does the impact of a two-stage air pollution control policy on air quality different? Evidence from 258 cities in China. *Atmos. Pollut. Res.* 15 (7), 102148. doi:10.1016/j.apr.2024.102148
- Li, M., Huang, Y., and Han, M. (2019). How to maintain a sustainable environment? A spatial evolution of urban atmospheric pollution and impact factors in China. *Sustainability* 11 (16), 4376. doi:10.3390/su11164376
- Li, Q., Chai, S., and Chen, S. (2025). “Evaluation of the environmental efficiency of China's power generation industry considering carbon emissions and air pollution: an improved three-stage SBM-SE-DEA model,” in *Environment, development and sustainability* (Springer), 1–22.
- Liu, H., Alharthi, M., Atil, A., Zafar, M. W., and Khan, I. (2022a). A non-linear analysis of the impacts of natural resources and education on environmental quality: green energy and its role in the future. *Resour. Policy* 79, 102940. doi:10.1016/j.resourpol.2022.102940
- Liu, K., Wang, X., and Zhang, Z. (2022b). Assessing urban atmospheric environmental efficiency and factors influencing it in China. *Environ. Sci. Pollut. Res.* 29, 594–608. doi:10.1007/s11356-021-15692-7
- Lu, Y. Y., He, Y., Wang, B., Ye, S. S., Hua, Y., and Ding, L. (2019). Efficiency evaluation of atmospheric pollutants emission in Zhejiang Province China: a DEA-malmquist based approach. *Sustainability* 11 (17), 4544. doi:10.3390/su11174544
- Ma, X., Zhao, X., Zhang, L., Zhou, Y., and Chen, H. (2021). Spatial-temporal characteristics and influencing factors of atmospheric environmental efficiency in China. *Environ. Sci. Pollut. Res.* 28, 12428–12440. doi:10.1007/s11356-020-11128-w
- Miao, Z., Baležentis, T., Tian, Z., Shao, S., Geng, Y., and Wu, R. (2019a). Environmental performance and regulation effect of China's atmospheric pollutant emissions: evidence from “three regions and ten urban agglomerations”. *Environ. Resour. Econ.* 74, 211–242. doi:10.1007/s10640-018-00315-6
- Miao, Z., Chen, X., Baležentis, T., and Sun, C. (2019b). Atmospheric environmental productivity across the provinces of China: joint decomposition of range adjusted measure and luenberger productivity indicator. *Energy Policy* 132, 665–677. doi:10.1016/j.enpol.2019.06.019
- Mo, B., Hou, M., and Huo, X. (2024). The synergistic reduction effect of PM_{2.5} and CO₂: evidence from national key ecological functional areas in China. *Environ. Sci. Pollut. Res.* 31 (9), 13766–13779. doi:10.1007/s11356-024-32063-0
- Ozkan, O., Eweade, B. S., and Usman, O. (2024). Assessing the impact of resource efficiency, renewable energy R&D spending, and green technologies on environmental sustainability in Germany: evidence from a wavelet quantile-on-quantile regression. *J. Clean. Prod.* 450, 141992. doi:10.1016/j.jclepro.2024.141992
- Paramati, S. R., Shahzad, U., and Doğan, B. (2022). The role of environmental technology for energy demand and energy efficiency: evidence from OECD countries. *Renew. Sustain. Energy Rev.* 153, 111735. doi:10.1016/j.rser.2021.111735
- Rashid, A. A., See, K. F., and Yu, M. M. (2024). Measuring airline efficiency using a dynamic network data envelopment analysis in the presence of innovation capital. *Technol. Forecast. Soc. Change* 206, 123457. doi:10.1016/j.techfore.2024.123457
- Ren, F. R., Cui, Z., Ding, X., Zhang, X. R., Li, R. H., Yao, Q., et al. (2023). The co-benefit of emission reduction efficiency of energy, CO₂ and atmospheric pollutants in China under the carbon neutrality target. *Energy Strategy Rev.* 49, 101125. doi:10.1016/j.esr.2023.101125
- Shao, Z., Zheng, X., Zhao, J., and Liu, Y. (2025). Evaluating the health impact of air pollution control strategies and synergies among PM_{2.5} and O₃ pollution in Beijing-Tianjin-Hebei Region, China. *Environ. Res.* 274, 121348. doi:10.1016/j.envres.2025.121348
- Shu, L., Wang, T., Li, M., Xie, M., and Liu, J. (2024). Optimizing emission control strategies for mitigating PM_{2.5} and O₃ pollution: a case study in the Yangtze river Delta region of eastern China. *Atmos. Environ.* 319, 120288. doi:10.1016/j.atmosenv.2023.120288
- Song, M., An, Q., Zhang, W., Wang, Z., and Wu, J. (2012). Environmental efficiency evaluation based on data envelopment analysis: a review. *Renew. Sustain. Energy Rev.* 16 (7), 4465–4469. doi:10.1016/j.rser.2012.04.052
- Sueyoshi, T., and Yuan, Y. (2015). China's regional sustainability and diversified resource allocation: DEA environmental assessment on economic development and air pollution. *Energy Econ.* 49, 239–256. doi:10.1016/j.eneco.2015.01.024
- Świdwa-Urbańska, J., and Battle-Sales, J. (2021). Data quality oriented procedure, for detailed mapping of heavy metals in urban topsoil as an approach to human health risk assessment. *J. Environ. Manag.* 295, 113019. doi:10.1016/j.jenvman.2021.113019

- Tao, H., Tao, M., and Wang, R. (2022). Do education human capital and environmental regulation drive the growth efficiency of the green economy in China? *Sustainability* 14 (24), 16524. doi:10.3390/su142416524
- Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 130, 498–509. doi:10.1016/s0377-2217(99)00407-5
- Underdal, A. (2010). Complexity and challenges of long-term environmental governance. *Glob. Environ. Change* 20 (3), 386–393. doi:10.1016/j.gloenvcha.2010.02.005
- Uralovich, K. S., Toshmatovich, T. U., Kubayevich, K. F., Sapaev, I. B., Saylaubaevna, S. S., Beknazarova, Z. F., et al. (2023). A primary factor in sustainable development and environmental sustainability is environmental education. *Casp. J. Environ. Sci.* 21 (4), 965–975. doi:10.22124/CJES.2023.7155
- Varela-Candamio, L., Novo-Corti, I., and García-Álvarez, M. T. (2018). The importance of environmental education in the determinants of green behavior: a meta-analysis approach. *J. Clean. Prod.* 170, 1565–1578. doi:10.1016/j.jclepro.2017.09.214
- Veeravel, V., Sadharma, E. K. S., and Kamaiah, B. (2024). Do ESG disclosures lead to superior firm performance? A method of moments panel quantile regression approach. *Corp. Soc. Responsib. Environ. Manag.* 31 (1), 741–754. doi:10.1002/csr.2598
- Wang, H., Xie, Y., Xue, W., Yan, G., Lei, Y., and Wang, J. (2025a). Revealing sources for synergistic control of PM_{2.5}, O₃, and CO₂ in China: based on social costs of air pollution and climate impact. *J. Environ. Manag.* 374, 123964. doi:10.1016/j.jenvman.2024.123964
- Wang, K. L., Meng, X. R., Yang, L., Yang, B. C., Wang, J. M., and Cheng, Y. H. (2017). The regional differences, changing trends and causes decomposition of atmospheric pollution emissions efficiency of China's major industrial provinces. *China Environ. Sci.* 37 (3), 888–898.
- Wang, L., Chen, B., Ouyang, J., Mu, Y., Zhen, L., Yang, L., et al. (2025b). Causal-inference machine learning reveals the drivers of China's 2022 ozone rebound. *Environ. Sci. Ecotechnology* 24, 100524. doi:10.1016/j.ese.2025.100524
- Wang, Y. (2024). Power source and driving factors of green transformation of resource-based cities in China. *Econ. Geogr.* 44 (4), 75–84. doi:10.15957/j.cnki.jjdl.2024.04.008
- Wang, Y., Zhao, Y., Liu, Y., Jiang, Y., Zheng, B., Xing, J., et al. (2023). Sustained emission reductions have restrained the ozone pollution over China. *Nat. Geosci.* 16 (11), 967–974. doi:10.1038/s41561-023-01284-2
- Wu, X., Chen, Y., Zhao, P., Guo, J., and Ma, Z. (2020). Study of haze emission efficiency based on new cooperation data envelopment analysis. *Expert Syst.* 37 (4), e12466. doi:10.1111/essy.12466
- Wu, X., Guo, J., Wu, X., and Guo, J. (2021). "Inputs optimization to reduce the undesirable outputs by environmental hazards: a DEA model with data of PM_{2.5} in China," in *Economic impacts and emergency management of disasters in China* (Springer), 547–580.
- Xia, H., Ding, L., Yang, S., and Wu, A. (2020). Socioeconomic factors of industrial air pollutants in Zhejiang Province, China: decoupling and decomposition analysis. *Environ. Sci. Pollut. Res.* 27, 28247–28266. doi:10.1007/s11356-020-09116-1
- Xu, L., Shen, C., Chen, J., Pan, X., and Xiao, G. (2024). Efficiency evaluation and improvement pathway of sulfur-oxide emissions in European ports based on Context-dependent SBM-DEA model. *Mar. Pollut. Bull.* 208, 117002. doi:10.1016/j.marpolbul.2024.117002
- Yang, J., Wang, Y., Zhang, L., and Zhao, Y. (2025a). Investigating the response of China's surface ozone concentration to the future changes of multiple factors. *Atmos. Chem. Phys.* 25 (4), 2649–2666. doi:10.5194/acp-25-2649-2025
- Yang, W., and Li, L. (2018). Efficiency evaluation of industrial waste gas control in China: a study based on data envelopment analysis (DEA) model. *J. Clean. Prod.* 179, 1–11. doi:10.1016/j.jclepro.2017.12.277
- Yang, Z., Li, Z., Cheng, F., Lv, Q., Li, K., Zhang, T., et al. (2025b). Two-decade surface ozone (O₃) pollution in China: enhanced fine-scale estimations and environmental health implications. *Remote Sens. Environ.* 317, 114459. doi:10.1016/j.rse.2024.114459
- Ye, F. F., and Wang, Y. M. (2019). Strategy selection of regional cooperative governance in air pollution: game analysis based on weighted DEA. *J. Syst. Sci. Math. Sci.* 39 (01), 37–50.
- Zadmirzaei, M., Hasanzadeh, F., Susaeta, A., and Gutiérrez, E. (2024). A novel integrated fuzzy DEA-artificial intelligence approach for assessing environmental efficiency and predicting CO₂ emissions. *Soft Comput.* 28 (1), 565–591. doi:10.1007/s00500-023-08300-y
- Žalėnienė, I., and Pereira, P. (2021). Higher education for sustainability: a global perspective. *Geogr. Sustain.* 2 (2), 99–106. doi:10.1016/j.geosus.2021.05.001
- Zhang, N., Sun, F., and Hu, Y. (2024). Carbon emission efficiency of land use in urban agglomerations of Yangtze River economic belt, China: based on three-stage SBM-DEA model. *Ecol. Indic.* 160, 111922. doi:10.1016/j.ecolind.2024.111922
- Zhang, Q., Ye, S., Ma, T., Fang, X., Shen, Y., and Ding, L. (2023). Influencing factors and trend prediction of PM_{2.5} concentration based on STRIPAT-scenario analysis in Zhejiang Province, China. *Environ. Dev. Sustain.* 25 (12), 14411–14435. doi:10.1007/s10668-022-02672-1
- Zheng, Z. (2021). Energy efficiency evaluation model based on DEA-SBM-Malmquist index. *Energy Rep.* 7, 397–409. doi:10.1016/j.egyrs.2021.10.020
- Zhou, W., Zhuang, Y., and Chen, Y. (2023). Spatial convergence and transfer path of atmospheric emission efficiency: an empirical analysis from China. *J. Clean. Prod.* 414, 137675. doi:10.1016/j.jclepro.2023.137675
- Zofio, J. L. (2007). Malmquist productivity index decompositions: a unifying framework. *Appl. Econ.* 39 (18), 2371–2387. doi:10.1080/00036840600606260