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Influencing factors and trend prediction of $PM_{2.5}$ concentration based on STRIPAT-Scenario analysis in Zhejiang Province, China

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Abstract

The government's development of eco-environmental policies can have a scientific foundation thanks to the fine particulate matter ($PM_{2.5}$) medium- and long-term change forecast. This study develops a STRIPAT-Scenario analysis framework employing panel data from 11 cities in Zhejiang Province between 2006 and 2020 to predict the changing trend of $PM_{2.5}$ concentrations under five alternative scenarios. The results reveal that: (1) urbanization development (*P*), economic development (*A*), technological innovation investment (*T*) and environmental regulation intensity have a significant inhibitory effect on $PM_{2.5}$ concentration in Zhejiang Province, while industrial structure, industrial energy consumption and the number of motor vehicles (*TR*) have a significant increase on $PM_{2.5}$ concentration. (2) Under any scenario, the $PM_{2.5}$ concentration of 11 cities in Zhejiang Province can reach the constraint target set in the 14th Five-Year plan. The improvement in urban $PM_{2.5}$ quality is most obviously impacted by the high-quality development scenario (S4). (3) Toward 2035, $PM_{2.5}$ concentrations of 11 cities in Zhejiang Province can reach the National Class I level standard in most scenario models, among which Hangzhou, Jiaxing and Shaoxing are under high pressure to reduce emissions and are the key areas for $PM_{2.5}$ management in Zhejiang Province. However, most cities cannot reach the 10 μg/m^3 limit of WHO's AQG2005 version. Finally, this study makes recommendations for reducing $PM_{2.5}$ in terms of enhancing industrial structure and funding science and technology innovation.

Keywords $PM_{2.5}$ · STRIPAT model · Scenario analysis · Ridge regression · Influencing factors

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1 Introduction

Fine particulate matter ($PM_{2.5}$) is an atmospheric environmental issue that academia takes extremely seriously and provides the basis for the strategy of socioeconomic development plans (Xu et al., 2023; Yan et al., 2022). Among them, long-term change prediction of $PM_{2.5}$ can provide scientific evidence and foundations for the development of government policies relating to energy conservation and emission reduction, industrial restructuring and ecological and environmental issues (Li et al., 2020; Xu et al., 2020). Since the State Council's *Action Plan for Prevention and Control of Air Pollution* was published and put into effect in September 2013, the problem of $PM_{2.5}$ pollution in China has been significantly alleviated (Xu et al., 2022). However, China's industrial, energy, transportation and other structural adjustment has just begun, and the structural pollution problem is still serious. The heavy chemical sector's industrial structure has not significantly changed over time, and the total consumption of coal remains high and continues to grow (He et al., 2022; Wu et al., 2021). In 2020, approximately 1/3 of the 337 cities with prefecture-level and above $PM_{2.5}$ concentrations still fall below the national Class II standard, and regional heavy pollution weather occurs occasionally. Therefore, it is crucial to investigate the socioeconomic causes of $PM_{2.5}$ concentration and forecast the trajectory because it serves as a legally mandated indicator of economic and social growth in the 14th Five-Year Plan (Su et al., 2022; Yue et al., 2020).

The concentrations of $PM_{2.5}$ are affected by several elements. In addition to the influence of natural factors such as meteorological and topographic conditions on $PM_{2.5}$ concentrations (Wu et al., 2021; Xu et al., 2021), previous studies have revealed the extent to which different single categories of pollution sources (e.g., coal combustion, transportation or power plants) influence $PM_{2.5}$ concentrations in different regions. From the source analysis results, it includes mobile sources, domestic sources, dust sources, industrial sources and coal-fired sources, among which diesel and gasoline vehicles account for a large proportion of mobile sources, solvent use and auto repair and other service industries contribute to domestic sources, dust sources are road dust and construction dust, and cement construction materials industries make up a significant percentage of industrial sources (Chen et al., 2018; Li et al., 2018). The level and pattern of urban socioeconomic development are closely correlated with the sources mentioned above. It demonstrated how elements like population size, population density, level of urbanization, industrial structure, energy consumption, energy mix (coal consumption share), road density and foreign direct investment have significant effects on $PM_{2.5}$ pollution (Chen et al., 2018; Gupta et al., 2022; Wu et al., 2021; Xu et al., 2022). For example, Alameddine et al. (2016) concluded that factors such as traffic, vehicle type and road conditions have a significant impact on $PM_{2.5}$ pollution. Meanwhile, factors that include technological innovation progress, environmental regulation and pollution control funding have a positive ameliorating effect on $PM_{2.5}$ pollution (Chen et al., 2019; Xia et al., 2022; Xue et al., 2020). These studies have laid a solid foundation for deeper insight into the relationship between socioeconomic development and $PM_{2.5}$ and have provided a valuable scientific basis for regional environmental policy formulation (Su et al., 2022; Tao et al., 2020).

Total pollutant discharge control and mass concentration constraints are important top-level designs for current environmental management (Lu et al., 2020; Yang et al., 2019). On the basis of clarifying the source of pollution, the trend prediction of $PM_{2.5}$ concentration is favored by scholars. In terms of prediction modeling methods, the main ones are statistical regression models, numerical simulation prediction and machine learning prediction. For statistical analysis and prediction studies of the researched contaminants, statistical models primarily rely on historical data. Several statistical models are employed as the research methods, such as linear regression (such as general panel regression and spatial econometric regression models) and nonlinear regression and so on (Chen et al., 2019; Gupta et al., 2022; Wu et al., 2021). Statistical models have the advantages of being easy to use, relatively easy access to necessary data and flexible output factors, specifically such as land use regression models and geographic and time-weighted regression models (Gu et al., 2021; Xu et al., 2020). Based on the knowledge of atmospheric physics and atmospheric chemistry, the numerical prediction applies the knowledge of atmospheric dynamics to predict various substances in the air through the material conservation equation. The specific methods include CMAQ, CAMx, WRF-Chem, etc. (Djalalova et al., 2015; Fang et al., 2022; Weagle et al., 2018; Zhang et al., 2020). The numerical model can simulate the development of regional pollutants and predict air quality. Due to a large amount of calculation and lack of timeliness, it is not suitable for the prediction of monthly and annual average concentrations (Senthilkumar et al., 2022). Recent years have seen steady advancement in computer technology, artificial intelligence and machine learning theory. Consequently, some data mining and computing tools have been widely employed to estimate $PM_{2.5}$ mass concentration, such as various neural network models (Biancofiore et al., 2017; Zhao et al., 2019) and random forest regression (Senthilkumar et al., 2022; Su et al., 2022).

In summary, existing studies have revealed the drivers of $PM_{2.5}$ concentration in a relatively systematic and comprehensive way, but there are the following gaps to be further explored: (1) different econometric regression analysis and other models have been used to explore the socioeconomic drivers of $PM_{2.5}$ concentrations, but after the estimation of impact coefficients, there is no prediction and assessment for medium and long-term changes in $PM_{2.5}$ concentrations, which lacks scientific guidance for subsequent planning and policy formulation (Chen et al., 2018; Xia et al., 2022). (2) The existing prediction methods for $PM_{2.5}$ concentration are mainly time series models (daily scale), land use regression models and neural network models. These methods are useful for estimating accurate changes in $PM_{2.5}$ concentration numerically or spatially distributed, but they cannot systematically reflect the government departments' efforts and interventions to achieve realistic pollutant concentrations through target constraints and task decomposition of medium- and long-term national economic planning (Wang et al., 2021a). Thus, this study constructs the STRIPAT-Scenario analysis framework and sets up different scenario development models to predict and estimate the $PM_{2.5}$ concentrations changes in the medium and long term, which integrated the variables, in terms of socioeconomic and environmental factors defined in the 14th Five-Year Plan of each city.

The main contributions of this study are (1) the use of ridge regression analysis to estimate the results of the socioeconomically driven STRIPAT model of $PM_{2.5}$. It can overcome the instability and the unreasonable regression coefficients of ordinary least squares regression (OLS), which can maintain the systematicity and integrity of the estimation of $PM_{2.5}$ pollution impact factors (Cheng et al., 2017; He et al., 2022). (2) Scenario analysis methods are employed to predict the changes in $PM_{2.5}$ concentrations in the medium and long term. One of the prevalent methods for conducting studies on the attainment of air quality is scenario analysis, where decision-makers make qualitative or quantitative predictions of future air quality by setting up different development scenarios (Yue et al., 2020; Zhang et al., 2019). As a result, the predicted $PM_{2.5}$ concentration results are more in line with the actual conditions of urban development and facilitate environmental policymakers to constrain and manage environmental targets.

The framework of this paper is designed as follows: Sect. 2 introduces the STRIPAT model, ridge regression model and the data sources of variables. Section 3 analyzes the regression results and predicts the $PM_{2.5}$ concentration changes in 11 cities in Zhejiang Province from 2021 to 2035 based on the scenario analysis. Section 4 discusses the $PM_{2.5}$ concentration conditions in 11 cities under high environmental standards and proposes $PM_{2.5}$ environmental improvement recommendations.

2 Methodology and data

This section is organized with the following contents: the overview of the study area, the methodology (STRIPAT model and ridge regression analysis), variables and data source. The technical framework of the study is presented in Fig. 1.

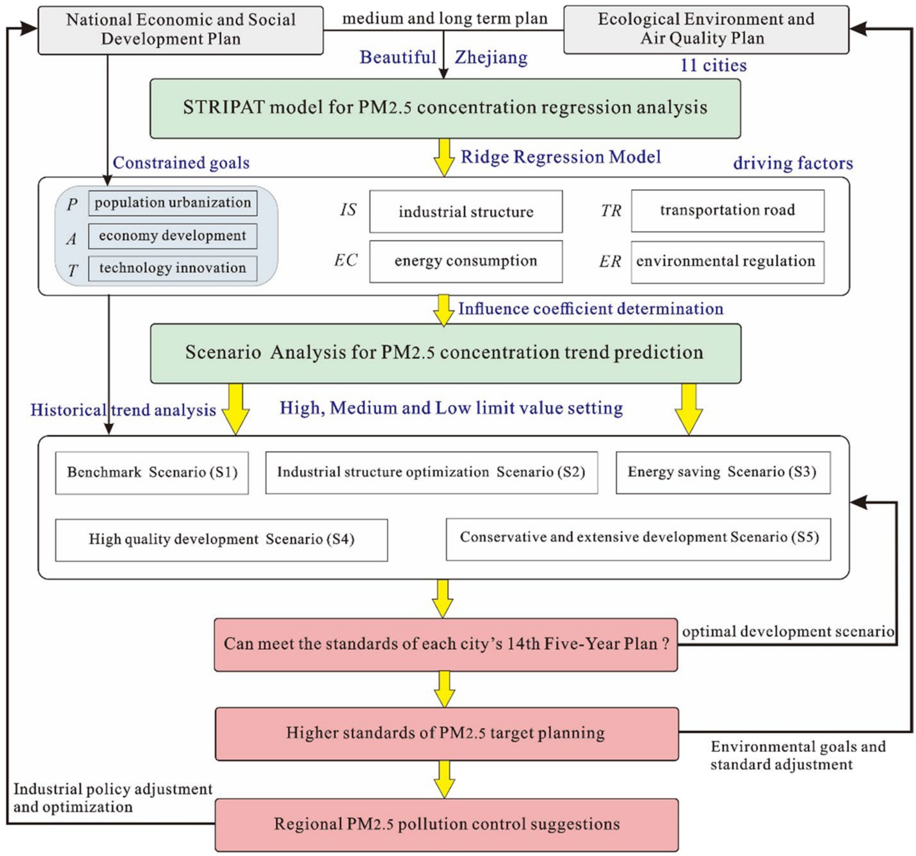

Fig. 1 The technical framework of this study

2.1 Study area

Although ranked one of China's most developed areas, Zhejiang Province is under intense pressure to reconstruct industrial structure, economic growth and environmental conservation (Jiang et al., 2019; Xia et al., 2020). Meanwhile, the foundation for continued air quality improvement in Zhejiang, as one of the most critical sectors of national air pollution prevention and management, is not stable enough, because the proportion of traditional high energy consumption and high pollution emission industries is still large, which poses a challenge to the continuous improvement of $PM_{2.5}$ quality in the future.

During the 14th Five-Year Plan period, Zhejiang Province will enter a new era of high-level socialist modernization and high-level construction, and a new journey of Beautiful Zhejiang. By 2035, the mission of Zhejiang is to create a high-quality leading demonstration area of Beautiful China and to essentially achieve the modernization of harmonious cohabitation between humans and nature (Ding & Fang, 2022). It also clarifies that the ambient air quality should be continuously improved, the "double control and double reduction" of $PM_{2.5}$ and ozone (O_3) should be realized, so the heavily polluted weather should be completely eliminated, and the moderately polluted weather should be basically eliminated. Among them, $PM_{2.5}$ concentration is one of the seven binding environmental indicators in the 14th Five-Year Plan of Zhejiang Province (Table 1). Reducing $PM_{2.5}$ concentration and improving ambient air quality is still a key task for each city. Figure 2 illustrates the map of urban regions in the study area.

2.2 STRIPAT model

The STRIPAT model is an extension of the IPAT model. Multiple independent variables related to population scale, structure and technology can be introduced into the model. The IPAT model has been widely used since it was proposed in the 1970s (Ehrlich &

Table 1 Comparison of expected constraint values of relevant indicators in the 14th Five-Year Plan of 11 cities in Zhejiang Province

City	*P* (%)		*A* (yuan)		*T* (%)		$PM_{2.5}$ (μg/m^3)	
	2020	2025	2020	2025	2020	2025	2020	2025
Hangzhou	83.6	86	136,617	180,000	3.59	4.0	30	Provincial target
Ningbo	78.4	80	132,614	170,000	2.86	3.6	23	<25
Wenzhou	72.8	75	71,766	100,000	2.29	3.0	25	<27
Jiaxing	71.3	75	102,541	150,000	3.31	3.5	28	<27
Huzhou	65.6	72	95,579	130,000	3.09	3.3	26	25
Shaoxing	71.5	75	113,746	150,000	2.58	3.3	28	30
Jinhua	68.7	74	95,431	130,000	2.01	2.8	28	Provincial target
Quzhou	58.1	70	72,192	100,000	1.79	2.8	26	<26
Zhoushan	71.9	75	130,130	200,000	1.74	2.7	17	<20
Taizhou	64.6	69	79,889	120,000	2.26	3.3	25	22
Lishui	61.8	70	61,811	100,000	1.83	3.0	21	23

Provincial target refers to the constraint index value determined by provincial government departments for the following cities, which is temporary to be determined

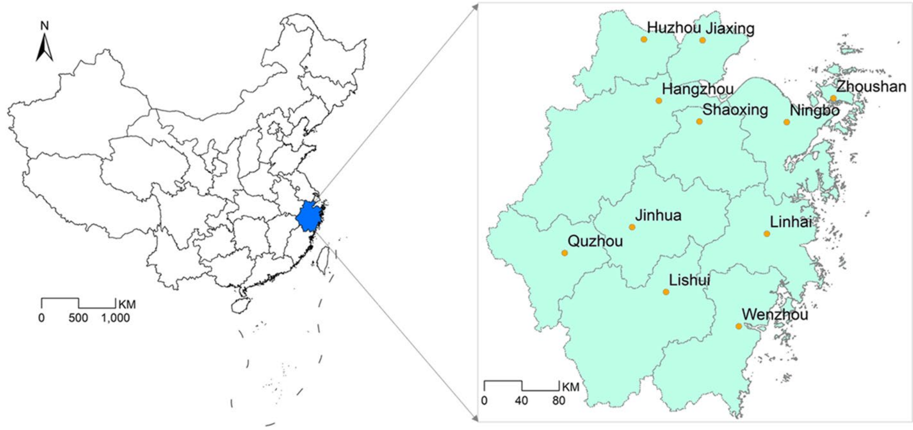

Fig. 2 Map of urban locations in the study area in Zhejiang Province

Holdren, 1971). The model can be used to study the impact of demographic, economic and technological factors on environmental pressure (Nosheen, 2021; Ma et al., 2017; Song et al., 2011; Wagoner et al., 2002). Its expression is as follows:

$$I = P \times A \times T \tag{1}$$

In the formula, I is the environmental pressure, including the consumption of resources and energy, greenhouse gas, pollutant emission and pollutant mass concentration, which refers to the annual average $PM_{2.5}$ concentration in the city in this study. P is generally the population size or population urbanization level, A is the regional affluence or economic development level, and T is the technical level.

However, the IPAT model has certain limitations. It defaults to those different factors that have the same impact on environmental pressure, contradicting the Environmental Kuznets Curve Hypothesis (Lin et al., 2009; York et al., 2003). To find the breakthrough of this model, Dietz and Rosa (1994) proposed the STIRPAT model based on the IPAT model, and its expression is as follows:

$$I = \alpha P^{\beta} A^{\gamma} T^{\lambda} \mu \tag{2}$$

In the model, α is the model coefficient, β, γ and λ represent the elastic coefficients of variables P, A and T, respectively, and μ is a random error term.

To eliminate the numerical dimensional influence of different variables, it is common to take logarithms on both sides of the above formula in the empirical analysis (Diao et al., 2018; Wang et al., 2017), which is:

$$\ln I = \ln \alpha + \beta \ln P + \gamma \ln A + \lambda \ln T + \ln \mu \tag{3}$$

The STIRPAT model rejects the assumption of unit elasticity and increases the randomness of model analysis, which is convenient for empirical analysis. Meanwhile, the STIRPAT model can also add a variety of factors affecting environmental pressure, such as environmental regulation, industrial structure and energy structure. Therefore, the STIRPAT model is the most commonly utilized in assessing the relationship between environmental pollution impact and numerous influencing factors, as evidenced by a significant number of empirical studies in the disciplines of carbon emission, pollutant emission and air quality (Diao et al., 2018; Liu & Xiao, 2018).

Existing research show that elements such as population size, economic development level, industrial structure, energy consumption, technological innovation, environmental regulation and transportation are commonly used in the analysis of air quality impacting factors, which can significantly affect the concentration of $PM_{2.5}$. Therefore, this study selects these six factors as the socioeconomic driving factors affecting $PM_{2.5}$ concentration and constructs an extended STIRPAT model, whose expression is:

$$\begin{aligned} \ln \mathrm{PM}_{2.5} = {} & \ln \alpha + \beta \ln P + \gamma \ln A + \delta (\ln A)^2 + \lambda \ln T + \rho \ln \mathrm{IS} + \theta \ln \mathrm{EC} \\ & + \xi \ln \mathrm{TR} + \sigma \ln \mathrm{ER} + \ln \mu \end{aligned} \tag{4}$$

where $PM_{2.5}$ is the average annual $PM_{2.5}$ concentration in the city, P stands for the population size (stated in terms of population urbanization rate), A represents the per capita GDP, T represents the technical level (expressed by the proportion of R & D investment in GDP here), IS stands the industrial structure (the chosen data is the percentage of industrial added value in GDP, revealing the influence of the effect of industrial source pollution on $PM_{2.5}$ concentration), EC is the intensity of energy consumption (expressed here in terms of comprehensive energy consumption of industries above designated size), TR is the traffic structure (expressed here in terms of urban motor vehicle ownership, reflecting the impact of traffic source pollution on $PM_{2.5}$ concentration), and ER is the intensity of environmental regulation (expressed here in terms of current operating expenses of industrial waste gas treatment facilities). β, γ, δ, λ, ρ, θ, ξ, σ stand for the elastic coefficient of each variable, respectively, while μ is a random error term. Table 2 has an explanation of each model variable. According to research by York et al. (2003), the quadratic term of per capita GDP is additionally introduced to investigate the nonlinear link between $PM_{2.5}$ concentration and economic development and to determine if an inverted U-shaped connection of the Environmental Kuznets Curve exists.

2.3 Ridge regression analysis

Because there is always an internal link between the socioeconomic variables influencing $PM_{2.5}$ concentration, this is referred to as multicollinearity. To maintain the integrity of explanatory variables, the ridge regression analysis method is introduced based on Formula (4) (Roberts & Martin, 2005; Tao et al., 2020). Hoerl first proposed ridge regression in 1962, and further discussed the ridge regression model with Kennard in 1970. The result is that there are multiple collinearities between independent variables. Ridge regression is an improved ordinary least squares estimation. The least squares estimation is improved to eliminate the influence of collinearity, and the model estimation results are more practical and reliable (Hoerl & Kennard, 1970). The process of eliminating multicollinearity is a process of independent variable selection (Hoerl, 2020). The basic formula of ridge regression is as follows:

$$\boldsymbol{Y} = \boldsymbol{X}\beta(K) + \varepsilon \tag{5}$$

$$\beta(K) = \left(\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X} + KI\right)^{-1}\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{Y} \tag{6}$$

In the formula, $\boldsymbol{Y}$ is a $(n \times 1)$ matrix of the dependent variable which refers to the $PM_{2.5}$ concentration of each city. X is a matrix of $n \times p$, which consists of relevant explanatory

Table 2 Definition and variables' data summary

Variables	Symbols	Definition	Unit	References	Data source
$PM_{2.5}$	*I*	Annual average concentration of $PM_{2.5}$	μg/m^3	Zhang et al. (2019)	the atmospheric composition analysis group of Dalhousie University and the *Statistical Yearbook of Zhejiang Province*
Population urbanization level	*P*	percentage of the urban population in the total population	%	Gupta et al. (2022), Xu et al. (2022)	*the Statistical Yearbook of Zhejiang Province* and *the Statistical Yearbook of Zhejiang Natural Resources and Environment* from 2007 to 2020
Economic development level	*A*	Resident population per capita GDP	CNY	Wang et al. (2021a), Li et al. (2020)	
Technology innovation	*T*	Proportion of R&D expenditure in GDP	%	Xia et al. (2022), Chen et al. (2019)	
Industrial structure	*IS*	Share of the secondary industry output value over the total GDP	%	He et al., 2022, Wu et al., (2021)	
Energy consumption	EC	Comprehensive energy consumption in the industrial sector	10^4 Tons of standard coal	Xia et al., (2022), Chen et al., (2018)	
Transportation road	TR	Urban motor vehicle ownership	Number	Gallego et al., (2013), Meng et al., (2021)	
Environmental regulation	ER	Current operating expenses of industrial waste gas treatment facilities	10^4 Yuan	He et al., (2022), Xia et al., (2022)	

variables affecting $PM_{2.5}$ concentration. B is the p × 1-dimensional regression coefficient; ε is a random disturbance term. Variable I is the identity unit matrix; K is the variable ridge regression coefficient in ridge traces. The choice of K is critical for the ridge regression model since the model's success is dependent on the ridge parameter K (ranging from 0 to 1). The reasonable value of K is usually determined according to the stable point of the ridge trace map. In the ridge trace map, if the correlation coefficient tends to be stable after a certain point, the K value corresponding to that point is the best K value of the model. At the same time, the smaller the K value, the better the fitting effect of the model (Marquardt & Snee, 1975; Wang et al., 2019; Zhao et al., 2022). After determining the best K value, the K value can be actively entered into the model to acquire the ridge regression model's estimated result.

2.4 Variables and data

The sources of $PM_{2.5}$ concentration data are diverse, mainly including the inversion estimation of atmospheric composition from satellite remote sensing and the measured value on the ground-based observations (Gu et al., 2021; Rahman & Thurston, 2022). China did not include the $PM_{2.5}$ index into the scope of routine air quality monitoring before 2012, resulting in the lack of measured value of $PM_{2.5}$. To maintain the continuity of data, the average annual $PM_{2.5}$ concentration value in each city from 2006 to 2012 is obtained from the aerosol estimates data of the atmospheric composition analysis group of Dalhousie University, Canada (Weagle et al., 2018; Yang et al., 2021). The average annual $PM_{2.5}$ concentration in each city from 2013 to 2019 comes from the measured values of urban environmental monitoring stations, specifically from the *Statistical Yearbook of Zhejiang Province*. Therefore, to keep the caliber of the two different data sources unified and better reflect the actual situation of urban $PM_{2.5}$ concentration, the correlation coefficient is obtained by dividing the measured $PM_{2.5}$ value in each city from 2013 to 2019 and the estimated value of atmospheric composition from 2013 to 2019. And then, the correlation coefficient is multiplied by the estimated value of atmospheric composition from 2006 to 2012 to approximately estimate the final average annual $PM_{2.5}$ concentration from 2006 to 2012. Figure 3 shows the final variation characteristics of $PM_{2.5}$ concentration in 11 cities in Zhejiang Province.

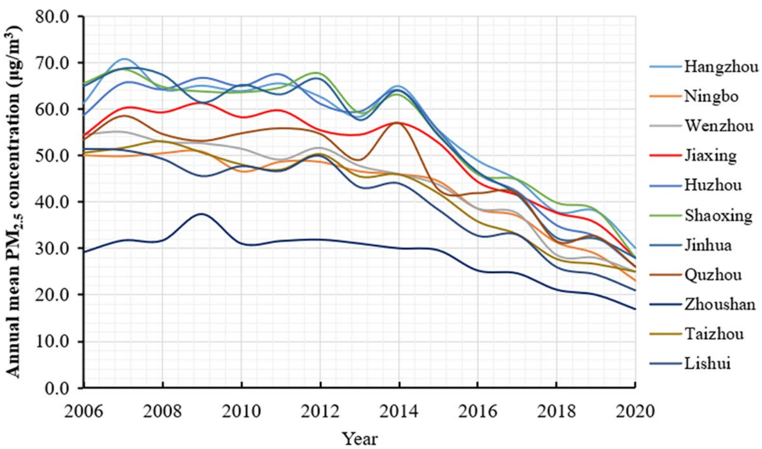

Fig. 3 Variation characteristics of $PM_{2.5}$ concentration in Zhejiang from 2006 to 2020

Data for the seven socioeconomic indicators were compiled from *the Zhejiang Province Statistical Yearbook* and *the Zhejiang Natural Resources and Environment Statistical Yearbook* from 2007 to 2020. Some missing data are filled with linear interpolation. Figure 4 depicts the box statistical findings of each index variable after taking the logarithm.

3 Results

3.1 STIRPAT model regression of $PM_{2.5}$ concentration

According to the collected index data, the linear STIRPAT of Formula (4) is selected as the analysis model (He et al., 2022). To facilitate the explanation, Hangzhou is taken as the case area for multiple regression analysis, utilizing the SPSS25 software. The outcomes are displayed in Table 3. Table 3 demonstrates significant multicollinearity between the variables, with the variance expansion factor much greater than 10 and the logarithm coefficient of per capita GDP and logarithm quadratic term coefficient of per capita GDP having variance expansion factors as high as 3402 and 3680, respectively. From the significance level of each explanatory variable, only ln*IS* and ln*TR* passed the significance test of 5% and 1%, respectively, and the regression coefficient is positive. This suggests that there is a negative relationship between $PM_{2.5}$ concentration and pollutant emissions brought on by the high percentage of industrial output value and the increasing number of motor vehicles, while having a significant positive promoting effect on air quality, which will aggravate $PM_{2.5}$ pollution. However, the other six variables did not pass the significance test. Therefore, the coefficients fitted by the OLS method cannot be reliably guaranteed and cannot be judged according to the fitting results of the OLS method. The multicollinearity of independent variables must be eliminated to obtain robust results.

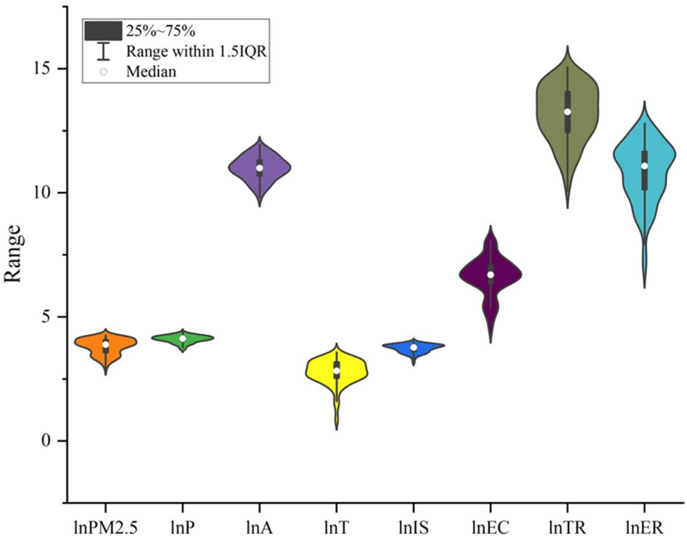

Fig. 4 Violin with box statistics of variables

Table 3 Ordinary least squares regression estimation results in Hangzhou

Variable	Unstandardized coefficients		standardized coefficients	*t*–Statistic	Sig	Collinear statistics	
	B	Std. Error	Beta			Tolerance	VIF
Cons	− 0.738	6.288			0.910		
ln*P*	− 2.802	1.551	− 0.583	− 1.807	0.114	0.034	29.137
ln*A*	1.281	0.327	0.743	1.845	0.276	0.002	3402.500
$(\ln A)^2$	− 0.023	0.014	− 0.791	− 1.597	0.154	0.015	3680.621
ln*T*	0.398	0.624	0.154	0.638	0.544	0.061	16.351
ln*IS*	1.898	0.486	1.220	3.901	0.006	0.037	27.327
ln*EC*	0.223	0.291	0.081	0.765	0.469	0.320	13.122
ln*TR*	0.814	0.343	1.738	2.372	0.049	0.007	150.113
ln*ER*	− 0.146	0.155	− 0.192	− 0.942	0.378	0.086	11.681

R^2 = 0.975, *F*- Statistic is 38.953, Sig. = 0.000. Other cities also have similar collinearity issues, which are not listed here

3.2 Ridge regression analysis of $PM_{2.5}$ concentration

To avoid multicollinearity among influencing factors, based on the extended STIRPAT model, this study fitted $PM_{2.5}$ concentration and influencing factors through ridge regression analysis and constructed $PM_{2.5}$ concentration prediction models for 11 cities in Zhejiang Province. Table 4 displays the relevant ridge regression results.

Thus, the $PM_{2.5}$ concentration prediction model of 11 cities in Zhejiang Province can be obtained. For example, in the ridge regression model, when $k = 0.14$, the regression coefficients of various influencing factors in Hangzhou tend to be stable. At this time, $R^2 = 0.92$, F value is 11.532, which is significant at the 1% level, so the overall fitting is better. The specific model equation is:

$$\begin{aligned} \ln \mathrm{PM}_{2.5} = {} & 7.472 - 1.031 \ln P - 0.052 \ln A - 0.003(\ln A)^2 - 0.257 \ln T \\ & + 0.719 \ln \mathrm{IS} + 0.087 \ln \mathrm{EC} + 0.008 \ln \mathrm{TR} - 0.061 \ln \mathrm{ER} \end{aligned} \tag{7}$$

For Hangzhou, urbanization development (*P*), economic development (*A*), technological innovation investment (*T*) and environmental regulation intensity (ER) have a substantial inhibitory impact on $PM_{2.5}$ concentration, while industrial structure (IS), industrial energy consumption (EC) and the number of motor vehicles (TR) have a significant increase on $PM_{2.5}$ concentration. Among them, the percentage of industrial production value has the most effect on $PM_{2.5}$ concentration. For every 1% increase in IS, $PM_{2.5}$ concentration will increase by 0.719%. Therefore, boosting the growth of the tertiary and high-tech industries, continuously reducing the proportion of industrial output value and strictly controlling the emission of industrial pollution sources are vital to improving the $PM_{2.5}$ environment in Hangzhou. Meanwhile, the per capita GDP and its quadratic term coefficient (significant at the negative and 10% levels) demonstrated an inverted U-shaped relationship between $PM_{2.5}$ concentration and economic development in Hangzhou. That is, economic development will first increase and subsequently decrease $PM_{2.5}$ concentrations, eventually improving air quality. This means that the current socioeconomic development model of Hangzhou (pursuing a digital economy

Table 4 Ridge regression fitting results of $PM_{2.5}$ concentration in Zhejiang Province

City	ln*P*	ln*A*	(ln*A*)^2	ln*T*	ln*IS*	ln*EC*	ln*TR*	ln*ER*	Cons	*k*	R^2
Hangzhou	-1.031^{**}	-0.052^{*}	-0.003^{**}	-0.257^{**}	0.719^{***}	0.087^{**}	0.008^{***}	-0.061^{**}	7.472^{***}	0.14	0.92
Ningbo	-2.109^{**}	0.133^{**}	-0.006^{*}	-0.117^{**}	0.860^{**}	0.417^{**}	0.063^{*}	-0.127^{**}	5.793^{***}	0.08	0.90
Wenzhou	-0.016^{***}	-0.180^{*}	-0.012^{*}	-0.067^{**}	0.720^{*}	0.168^{**}	0.005^{***}	-0.097^{**}	4.482^{***}	0.04	0.84
Jiaxing	-1.902^{**}	0.008^{**}	-0.002^{***}	-0.351^{**}	0.399^{**}	0.072	0.069^{**}	-0.087^{**}	10.856^{***}	0.06	0.85
Huzhou	-0.877^{**}	-0.101^{*}	-0.005^{**}	0.055^{*}	1.397^{*}	0.092^{*}	0.063^{*}	-0.003^{***}	1.746^{***}	0.16	0.90
Shaoxing	-1.473^{*}	-0.049^{**}	-0.002^{**}	-0.064^{***}	0.540^{*}	0.312^{**}	0.317^{**}	-0.081^{**}	2.842^{***}	0.20	0.89
Jinhua	-2.273^{*}	-0.027^{***}	-0.003^{**}	-0.055^{*}	1.283^{*}	0.419^{*}	0.046^{**}	-0.020^{**}	6.131^{***}	0.06	0.93
Quzhou	-0.312^{**}	-0.011^{***}	-0.001	-0.086^{*}	1.368^{*}	0.222^{**}	-0.015	-0.129^{*}	3.031^{***}	0.10	0.92
Zhoushan	-3.372^{*}	-0.038^{***}	-0.005^{**}	-0.008^{***}	0.570^{**}	0.130^{**}	0.098^{*}	-0.041^{**}	14.887^{***}	0.04	0.80
Taizhou	-0.395^{**}	-0.047^{**}	-0.003^{**}	-0.091^{**}	0.136^{**}	0.684^{*}	0.013^{***}	-0.053^{*}	1.367^{***}	0.12	0.88
Lishui	-0.230^{**}	-0.022^{***}	-0.001^{***}	-0.009^{***}	0.759^{*}	0.203^{**}	-0.062	-0.073^{**}	3.599^{***}	0.26	0.95

* * *, * * and * represent $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively direction and leading the efficiency of pollution management with science and technology) is advantageous to the development of the $PM_{2.5}$ environment.

Similarly, through the regression fitting results of $PM_{2.5}$ concentration in other 10 cities, it has been discovered that *P*, *A*, *T* and ER significantly reduce $PM_{2.5}$ concentration. However, the significance level and effect coefficient of various cities vary to some extent, even though IS, EC and TR have a definite growing effect on $PM_{2.5}$ concentration. In contrast, the influence coefficient of IS on $PM_{2.5}$ concentration is generally higher than EC and TR, which means that a higher proportion of industrial output value and higher industrial pollution emissions are important factors leading to the increase of $PM_{2.5}$ concentration in Zhejiang. Thus, accelerating industry structural adjustment and decreasing industrial energy consumption are critical to improving $PM_{2.5}$ quality in Zhejiang Province in the future (Jiang et al., 2019; Xu et al., 2021). Among the indicators of restraining $PM_{2.5}$ concentration, the impact coefficient of urbanization level (*P*) is higher than *A* and *T*. On the one hand, it indicates that the current urbanization construction process in Zhejiang aims at building a green and harmonious livable city and realizing the synchronous improvement of $PM_{2.5}$ environmental quality in the process of the urban agglomeration of population. It is vital to improve the urban environment through scientific and technological means such as the digital economy and urban brain. On the other hand, it also implies that the $PM_{2.5}$ pollution management path fueled by scientific and technological innovation in Zhejiang Province has significant untapped potential, which is also a key breakthrough direction for $PM_{2.5}$ quality improvement in the future (Ding & Fang, 2022; Xia et al., 2020).

In addition, the quadratic coefficient of per capita GDP in Quzhou city did not pass the significance test, while other cities passed the significance test at least at the level of 10%, which indicates that, with the exception of Quzhou, there is an inverted U-shaped link between $PM_{2.5}$ concentration and economic growth. The effect of TR on $PM_{2.5}$ concentration in Quzhou and Lishui did not pass the negative significance test. The effect of ER on $PM_{2.5}$ concentration in Jiaxing did not pass the positive significance test. It is worth noting that as an industrial city with a developed traditional manufacturing industry, Jiaxing's industrial energy consumption has been increasing. The amount of normal coal consumed in 2020 stayed at 16.25 million tons. Effective action is currently required to slow down the pace of economic expansion, achieve energy conservation and emission reduction and lower the usage of petrochemical energy sources like coal. Further, the scientific and technological innovation level (*T*) of Huzhou and Lishui has a beneficial growing influence on the $PM_{2.5}$ concentration, which may be attributed to the two cities' lack of investment in science and technology. It resulted in the lack of influence of science and technology on the $PM_{2.5}$ emission reduction.

3.3 Scenario analysis of $PM_{2.5}$ concentration trend prediction

3.3.1 Scenario mode setting of $PM_{2.5}$ concentration trend

According to the regression results of the above analysis, this paper sets 3 values, which are low, medium and high, for the change rate of the 7 factors in each city's prediction model. In the median value, the change rates of *P*, *A* and *T* influencing factors in cities from 2021 to 2025 are set on average according to the binding objectives in the 14th Five-Year Plan, and the change rates of other indicators and influencing factors in cities after 2026 are set according to the change trends of population, economy, energy and other relevant policies and historical data. In the low and high values, the setting of

Table 5 Change rate setting of influencing factors of $PM_{2.5}$ concentration in Zhejiang Province

Change rate	Time	Setting of change rate						
		P	*A*	*T*	*IS*	*EC*	*TR*	*ER*
Low	2021–2025	EPV	EPV	EPV	− 1.60%	− 1.5%	7.00%	7.00%
	2026–2030	0.50%	4.00%	1.50%	− 1.40%	− 1.0%	5.00%	5.00%
	2031–2035	0.25%	3.00%	0.50%	− 1.20%	− 0.5%	3.00%	3.00%
Medium	2021–2025	EPV	EPV	EPV	− 2.00%	− 3.0%	11.00%	13.00%
	2026–2030	1.00%	6.00%	2.20%	− 1.80%	− 2.0%	9.00%	10.00%
	2031–2035	0.75%	5.00%	1.70%	− 1.60%	− 1.0%	7.00%	7.00%
High	2021–2025	EPV	EPV	EPV	− 2.40%	− 5.0%	15.00%	20.00%
	2026–2030	1.50%	8.00%	4.50%	− 2.20%	− 3.0%	13.00%	15.00%
	2031–2035	1.00%	7.00%	3.00%	− 2.00%	− 1.0%	11.00%	10.00%

The values of *P, A* and *T* take the Five-Year average value of the adjustments of each city in relation to the objectives of *the 14th Five-Year Plan for National Economic and Social Development and the Outline of Long-term Objectives for the Year 2021–2025*, named Expected Planning Value (EPV). *IS* and *EC* are in the process of transformation and energy emission reduction, so their change rate is set to negative

Table 6 Scenario setting of $PM_{2.5}$ concentration change in cities in Zhejiang Province

Scenario	Setting of change rate						
	P	*A*	*T*	*IS*	*EC*	*TR*	*ER*
S1	Medium	Medium	Medium	Medium	Medium	Medium	Medium
S2	Medium	Medium	Medium	High	Medium	Medium	Medium
S3	Medium	Medium	Medium	Medium	High	Low	Low
S4	High	High	High	High	High	Low	High
S5	Low	Low	Low	Low	Low	High	Low

the change rate of each influencing factor is adjusted accordingly based on the median value. At the same time, this paper also takes into account the impact of COVID-19, economic globalization and other various factors in the new era (Chauhan & Singh, 2020; Du et al., 2021; Le Quéré et al., 2020). Among them, COVID-19 will have a long-term impact on the industrial structure and economic development, while other factors will be less affected. Therefore, the change rate of industrial structure is reduced based on the setting of relevant policies and historical data. The setting of the change rate for various influencing elements of $PM_{2.5}$ concentration change in Zhejiang Province is listed in Table 5.

According to the change rates of three influencing factors of low, medium and high in each city, five different scenario models are established to predict the changing trend of $PM_{2.5}$ concentration in each city in Zhejiang Province. Table 6 indicates the detailed settings of the five scenarios.

Benchmark scenario (S1) The change rate of each influencing factor selects the medium value. Combined with the 14th Five-Year Plan and the long-term goal of 2035, this scenario implicates the potential change trend of $PM_{2.5}$ concentration in the future under the development goals of per capita GDP, population, energy, urbanization and other relevant policies of cities, which aims to investigate the impact of cities on $PM_{2.5}$ concentration in the future in light of the existing planning guidelines (Zhang et al., 2020).

Industrial structure optimization scenario (S2) The change rate of industrial structure (*IS*) selects a high value (i.e., the fraction of industrial production value falls dramatically), and a medium value is chosen based on the pace of change of other relevant factors. This scenario reflects those cities further optimizing and upgrading their industrial structure on the basis of existing policies. Controlling pollution emissions from industrial sources is an important way to improve $PM_{2.5}$ concentration and promote China's sustainable development. Therefore, the air pollution control plan has been the subject of pertinent industrial structure transformation and upgrading programs from all levels of government. By adjusting the industrial structure, secondary industries, particularly traditional industries, will play a decreasing role in the national economic growth, while high-tech, the digital economy and services will take over as the main drivers (Li et al., 2018). Compared with the benchmark scenario, the proportion of industrial output value of each city will be further reduced.

Energy saving scenario (S3) The energy consumption intensity (*EC*) selects the high value while the change rate of traffic source intensity *TR* selects the low value, and the change rate of other influencing factors selects the medium value. Reducing the consumption of petrochemical energy such as coal and decreasing the emission of pollutants is the most important step toward strengthening the quality of the air environment. This scenario reflects that based on existing policies, cities should tighten their grip on energy-related regulations, spend more on energy efficiency and emission reduction, aggressively change their energy structures, advance technology, and cut back on energy-intensive activities and traffic-related emissions, to reduce $PM_{2.5}$ concentration (Yue et al., 2020).

High-quality development scenario (S4) The change rate of each influencing factor chooses the high value, while the rate of TR chooses the low value, so it is possible to slow down the growth rate of urban automobile traffic and control the emission of traffic exhaust. This scenario reflects those cities do not take the growth of total GDP as the main goal, but take the coordinated development of the social, economic and environmental system as the focus. During the procedure of new urbanization, cities are taking effective measures to achieve green development and improve $PM_{2.5}$ environmental quality, such as increasing investment in scientific and technological innovation, applying energy conservation and emission reduction measurements (significantly reducing industrial energy), optimizing industrial structure (dramatically decreasing the percentage of industrial output value, especially the reduction of pollution-intensive industrial sectors), strengthening environmental pollution control and other measures.

Conservative and extensive development scenario (S5): the change rate of each influencing factor selects the low value, except that *TR* selects the high value. This scenario reflects that affected by the global epidemic, the socioeconomic development of these regions slows down (Wang et al., 2021b), the urbanization level and per capita GDP is at a low value, as well as a reduction in expenditure on scientific and technological innovation. Furthermore, throughout this phase, the industrial structure adjustment has slowed down and the industrial energy consumption has remained high. There are fewer restrictions on the number of motor vehicles, the handling of traffic-related pollution is inadequate, and less emphasis is placed on changes in air pollution emissions and $PM_{2.5}$ concentrations. Thus, economic growth is a relatively extensive and conservative method (Liu & Xiao, 2018; Narayan et al., 2016).

3.3.2 Scenario analysis results of $PM_{2.5}$ concentration trend

Based on the regression prediction model of $PM_{2.5}$ concentration change in each city, combined with five scenario settings, this study calculated the $PM_{2.5}$ concentration change of each city from 2021 to 2035 under different scenarios (Fig. 5). Besides, the study predicted the time when each city meets the $PM_{2.5}$ concentration constraint target set by the government and meets the 14th Five-Year Plan standard under different scenarios (Table 7).

Figure 5 shows that the $PM_{2.5}$ concentrations in each city decreased to different degrees under different scenario models. The decrease of $PM_{2.5}$ concentration is S4 > S3 > S2 > S1 > S5. Thus, the High-quality development scenario (S4) has the most obvious effect on the improvement of urban $PM_{2.5}$ quality, while S1 and S5 scenarios are relatively weak in the improvement of urban $PM_{2.5}$ quality. It can be seen from this: (1) accelerating the transformation of industrial structure, reducing energy usage and focusing on green development will result in a rapid reduction in $PM_{2.5}$ concentrations; On the contrary, if the economy is developed in a sloppy manner, the investment in science and technology innovation is slowed down, and the control of pollution emission is reduced, the reduction of $PM_{2.5}$ concentration will be hindered. (2) The effect of energy consumption reduction and motor vehicle quantity control (traffic source pollution emission reduction) in the S3 scenario on urban $PM_{2.5}$ quality improvement is better than the effect of industrial restructuring alone on $PM_{2.5}$ concentration. The purpose of industrial restructuring is also to regulate and reduce energy usage, such as coal consumption, which in turn achieves the control of air pollutant emissions to benefit the $PM_{2.5}$ quality.

To test the accuracy of the $PM_{2.5}$ concentration prediction results of the scenario analysis, the ground-level measured $PM_{2.5}$ concentrations in each city in 2021 are compared with the predicted $PM_{2.5}$ concentrations of different scenarios here (Table 7). It was found that the overall $PM_{2.5}$ concentration prediction accuracy for different scenarios showed that S5 > S1 > S2 > S3 > S4, and this order is the opposite of the previous ranking of the decreasing trend of $PM_{2.5}$ concentration. Thus, affected by the epidemic, urban industrial restructuring and energy consumption reduction slow down accordingly, and the operating costs of air pollution treatment also slow down, resulting in the changes in $PM_{2.5}$ concentration also slowing down, basically following the evolutionary path of S5 and S1. This is also in line with the current actual situation. Therefore, in the 14th Five-Year Plan (Table 1), Shaoxing, Zhoushan, Lishui and other cities preset the $PM_{2.5}$ concentration in 2025 to be slightly higher than the initial concentration in 2020, retaining sufficient room for future socioeconomic development. Taking into account the various socioeconomic growth frameworks of various cities, the environmental planning policies should be formulated in light of the real circumstances of urban development to fulfill the dual goals of economic growth and environmental quality improvement. So, it is suggested that the $PM_{2.5}$ concentration control should be implemented in a stepwise progressive model: that is, Zhejiang Province can choose the S1 baseline scenario or the S5 conservative economic development scenario during 2021–2025, and gradually make good reserves of science and technology, talents, capital and other factors for industrial structure transformation and upgrading. Then, choose the S2 or S3 green development model during 2026–2030, which on the basis of S1, continually improves the industrial structure and layout, minimizes industrial energy consumption, optimizes the industrial structure and layout, and minimizes industrial energy consumption on a constant basis. And finally, it pursues the S4 high-quality development scenario during 2031–2035.

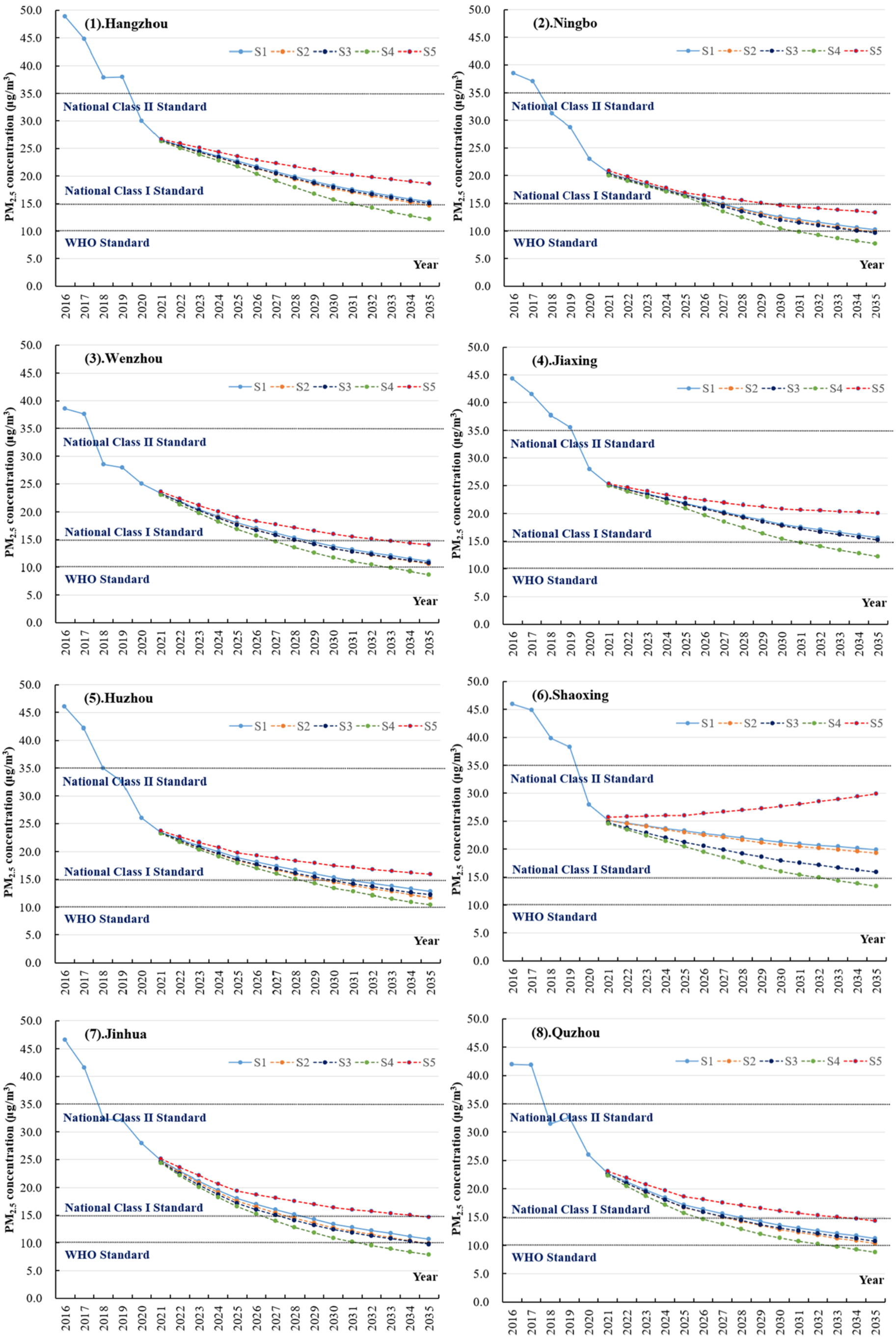

Fig. 5 $PM_{2.5}$ concentration forecast of 11 cities in Zhejiang Province

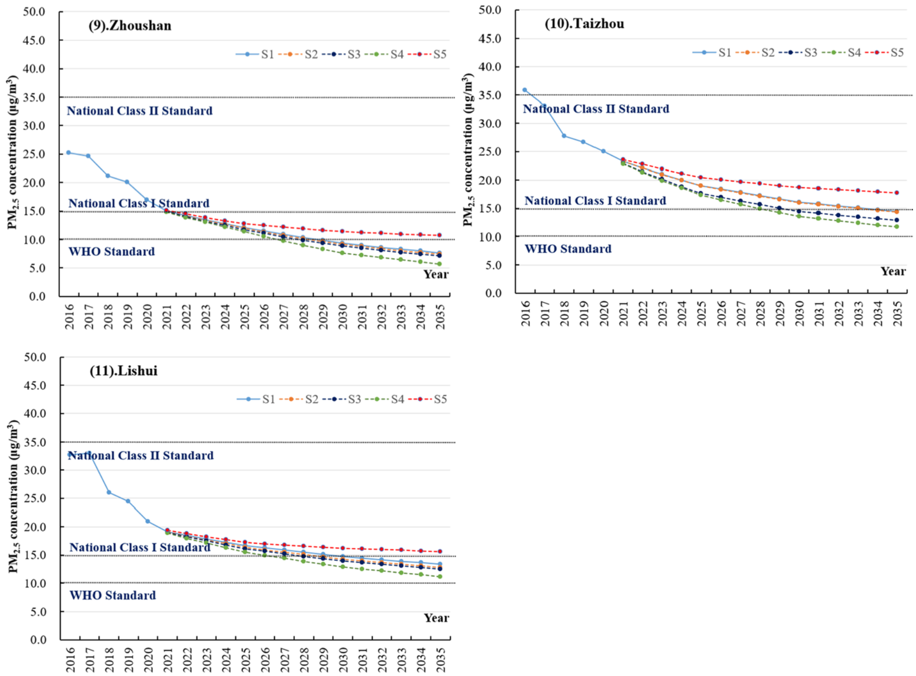

Fig. 5 (continued)

It can also be found that regardless of the scenario model, by 2025, the $PM_{2.5}$ concentrations in all 10 cities, except Zhoushan, do not fulfill the key national requirements for ambient air quality.

4 Discussion and policy implication

4.1 Higher standard of $PM_{2.5}$ target planning

Combining the results of Table 1 and Table 7, it can be seen that according to the current socioeconomic development trend, the $PM_{2.5}$ concentration in each city can reach the constraint target set in the 14th Five-Year Plan. However, for the long-term development of 2035, in the process of pursuing higher quality economic development and a beautiful ecological environment, what development path should be taken if the higher standard $PM_{2.5}$ limits for environmental constraints have been involved, such as National Class I level standard and WHO standard?

Table 8 shows the earliest occurrence time when $PM_{2.5}$ concentration in 11 cities in Zhejiang province meets the National Class I standard and WHO standard (AQG 2005) under different scenarios.

The accompanying table shows that there are significant disparities in the occurrence periods of $PM_{2.5}$ concentrations meeting the National Class I level standard and the WHO standard in different cities. According to the time of reaching the standard, the 11 cities can be classified into three groups: (1) cities that are easy to control $PM_{2.5}$ concentrations.

Table 7 Comparison of measured and predicted $PM_{2.5}$ concentrations by cities in Zhejiang Province in 2021 under different scenarios and attainment of the standard in 2025

	Scenarios	HZ	NB	WZ	JX	HZ	SX	JH	QZ	ZS	TZ	LS
	2021 Measured value	28	21	25	26	25	27	27	26	15	23	21
S1	2021 Predictive value	26.52	20.47	23.31	25.16	23.43	25.17	24.81	23.74	14.98	23.25	19.13
	2021 Error rate	5.28%	2.52%	6.76%	3.23%	6.28%	6.77%	8.11%	8.69%	0.13%	1.09%	8.90%
	Reach the 2025 standard	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S2	2021 Predictive value	26.44	20.40	23.24	25.12	23.30	25.11	24.67	23.62	14.94	23.24	19.07
	2021 Error rate	5.57%	2.86%	7.04%	3.38%	6.80%	7.00%	8.63%	9.15%	0.40%	1.04%	9.19%
	Reach the 2025 standard	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S3	2021 Predictive value	26.47	20.25	23.23	25.13	23.33	24.71	24.54	23.63	14.88	22.92	19.01
	2021 Error rate	5.46%	3.57%	7.08%	3.35%	6.68%	8.48%	9.11%	9.11%	0.80%	0.35%	9.47%
	Reach the 2025 standard	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S4	2021 Predictive value	26.29	20.03	23.03	24.96	23.19	24.54	24.39	23.43	14.81	22.83	18.87
	2021 Error rate	6.11%	4.62%	7.88%	4.00%	7.24%	9.11%	9.66%	9.88%	1.26%	0.74%	10.1%
	Reach the 2025 standard	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S5	2021 Predictive value	26.73	20.87	23.57	25.35	23.65	25.74	25.16	24.12	15.12	23.59	19.37
	2021 Error rate	4.53%	0.62%	5.72%	2.50%	5.40%	4.66%	6.81%	7.23%	0.80%	2.56%	7.76%
	Reach the 2025 standard	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The smaller the error rate, the more accurate the $PM_{2.5}$ concentration prediction. HZ ~ LS represent the city of Hangzhou ~ Lishui, respectively

Table 8 The year to reach the National Class I level standard and WHO standard for $PM_{2.5}$ concentration in each city under different scenarios

City	National Class I level standard (15 μg/m^3)					WHO standard (10 μg/m^3, AQG 2005)				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
Hangzhou	–	2035	–	2031	–	–	–	–	–	–
Ningbo	2027	2027	2027	2026	2030	–	2035	2035	2031	–
Wenzhou	2029	2028	2028	2027	2033	–	–	–	2033	–
Jiaxing	–	–	–	2031	–	–	–	–	–	–
Huzhou	2031	2030	2030	2029	–	–	–	–	–	–
Shaoxing	–	–	–	2032	–	–	–	–	–	–
Jinhua	2029	2028	2028	2027	2034	–	2035	2035	2032	–
Quzhou	2028	2028	2028	2026	2034	–	–	–	2033	–
Zhoushan	2021	2021	2021	2021	2022	2029	2029	2028	2027	–
Taizhou	2034	2033	2030	2028	–	–	–	–	–	–
Lishui	2030	2029	2028	2026	–	–	–	–	–	–

"–" indicates that in this scenario, there is no year in which a city reaches the corresponding $PM_{2.5}$ environmental quality standard. The World Health Organization (WHO) AQG2005 version of 10 μg/m^3 is used here. In 2021, The World Health Organization (WHO) published the most recent global air quality recommendations (AQG2021), which set a $PM_{2.5}$ indicator limit of 5 μg/m^3

Before 2035, no matter what development scenario is followed, the $PM_{2.5}$ concentration of these cities can reach the National Class I standard. These cities are Zhoushan, Quzhou, Jinhua, Ningbo and Wenzhou. The $PM_{2.5}$ concentration of these cities is low, so the pressure of $PM_{2.5}$ emission reduction is relatively light. Benefiting from favorable natural geographical conditions and lower pollutant emissions, Zhoushan is the first city to reach the National Class I standard of $PM_{2.5}$ concentration in 2021. Other cities will not meet the National Class I standard until 2026 at the earliest. (2) Cities that are stable in control of $PM_{2.5}$ concentrations. Huzhou, Taizhou and Lishui can meet the national level standards in the other four scenarios except in the S5 scenario. These cities need to avoid taking the road of extensive development, adhere to the current direction of industrial adjustment and upgrading, and stabilize the investment of environmental protection funds for $PM_{2.5}$ governance. (3) Cities that are difficult in controlling $PM_{2.5}$ concentrations. Hangzhou, Jiaxing and Shaoxing, can meet the National Class I standard mainly under the S4 scenario. Among them, the proportion of energy consumption and traditional polluting industries in Jiaxing and Shaoxing has been high, including the rising number of motor vehicles and significant traffic exhaust pollution. These cities are under severe economic transition and development strain. They should rely on the digital economy as well as scientific and technical innovation to improve pollution management and lower the emission of air pollutants. Therefore, these cities are critical places of $PM_{2.5}$ control in Zhejiang Province.

By 2035, most cities will not be able to meet the 10 μg/m^3 limit of WHO's AQG 2005 version, and only the first category cities that easy to control the $PM_{2.5}$ concentrations will be able to meet the standard around 2035 in scenario models such as S4 and S3 (exceptionally, Zhoushan can be the first to meet the standard around 2028). Meanwhile, all cities are unable to meet the 5 μg/m^3 limit of WHO's AQG2021 version. Therefore, Zhejiang, as China's demonstration zone of ecological civilization, is in the process and context of achieving the province's high-quality dual goals, which promoting economic development and the construction of a clean air demonstration zone facing 2035. Zhejiang can try to constrain and assess the ecological environmental protection tasks of each city with higher environmental quality standards, making a more active contribution to building a beautiful Zhejiang and effectively enhancing the people's sense of happiness in enjoying the blue sky.

4.2 Regional $PM_{2.5}$ pollution control suggestions

Combining the results of different scenario analyses, the following pollution control measures for $PM_{2.5}$ are proposed, to achieve new progress in improving air quality.

(1) Optimize and adapt the industrial structure to reduce $PM_{2.5}$ pollutant emissions. From the regression analysis, IS has a significant positive effect on $PM_{2.5}$. Zhejiang needs to accelerate the relocation and transformation significantly polluting industries in densely populated metropolitan regions, mergers and acquisitions, reduce the production value of heavy polluting industrial sectors, direct the rational layout of essential industries such as petrochemicals, chemicals, iron and steel, building materials and nonferrous metals and ban the construction of new chemical parks. Strictly implement the requirements for capacity replacement in the steel, cement, flat glass and foundry industries, and continue to reduce and eliminate backward and excess capacity. Accelerate the implementation of textile, chemical fiber, pharmaceutical and chemical, metal products and other traditional industries' green technology transformation (Ding et al., 2020).

(2) Leading the pollution control of $PM_{2.5}$ by science and technology innovation. From the regression analysis, T has a significant reduction effect on $PM_{2.5}$, which means increasing investment in science and technology innovation is a necessary path for industrial structure transformation. Therefore, on the one hand, it is vital to increase the end treatment technology of air pollution, research and develop the coordinated control technology of $PM_{2.5}$ and ozone, develop the efficient treatment technology and equipment of flue gas and volatile organic pollutants, and research and develop the key treatment technologies such as the source substitution of raw and auxiliary materials with low VOCs and the key technologies for the prevention and management of mobile source air pollution. On the other hand, it is critical to rely on artificial intelligence and information technology, to expedite the integration and deployment of a new generation of digital technology, to significantly boost scientific and technical innovation capability, to upgrade and improve the three-dimensional monitoring network of atmospheric compound pollution and to systematically improve the $PM_{2.5}$ environmental management capabilities (Zhang et al., 2020).

(3) Reduce the exhaust emission of $PM_{2.5}$ with green traffic engineering. From the regression analysis, TR can significantly increase $PM_{2.5}$. Therefore, it is necessary to accelerate the green development of highway transportation and reduce particulate matter emissions when the total number of motor vehicles cannot be reduced. On the one hand, Zhejiang Province should continue to eliminate old vehicles. By 2025, it will basically eliminate the operating heavy diesel trucks with National Class III and below emission standards and accelerate the elimination of National Class IV standard diesel trucks. On the other hand, it is necessary to promote the use of new and clean energy non-road mobile machinery, and actively promote the elimination, replacement or clean transformation of high energy consumption and high pollution non-road mobile machinery. For the above-mentioned cities with difficulties in controlling $PM_{2.5}$ concentrations, it is

vital and necessary to accelerate the deployment of clean energy public transportation vehicles in large and medium-sized cities.

5 Conclusions

In terms of national economic and social planning and ecological and environmental planning, variations in $PM_{2.5}$ concentration over the long and medium term are significant binding indicators. In this study, a STRIPAT-Scenario analysis framework was constructed to predict the trends of $PM_{2.5}$ concentrations under five different scenarios based on panel data of 11 cities in Zhejiang from 2006 to 2020, and accordingly, to explore the compliance of each city with higher quality environmental standards. The regression results show that urbanization development (*P*), economic development (*A*), technological innovation input (*T*) and environmental regulation intensity (ER) had a significant inhibitory effect on $PM_{2.5}$ concentration in Zhejiang Province, while the number of motor vehicles (TR), industrial energy consumption (EC) and industrial structure (IS) have a considerable growing impact on $PM_{2.5}$ concentration.

The scenario analysis shows that the reduction of $PM_{2.5}$ concentration is S4 > S3 > S2 > S1 > S5, which is that the high-quality development scenario (S4) has the most obvious effect on the improvement of urban $PM_{2.5}$ quality. Under any scenario, the $PM_{2.5}$ concentrations of 11 cities in Zhejiang Province can reach the constraint objectives which is established in the 14th Five-Year Plan.

Toward 2035, $PM_{2.5}$ concentrations can reach the National Class I standard under most scenario models, but Hangzhou, Jiaxing, and Shaoxing are under stronger pressure to reduce emissions, which makes them key regions for $PM_{2.5}$ management in Zhejiang Province. It is worth noting that most cities cannot meet the 10 μg/m^3 limit of WHO's AQG2005 version. In the future, Zhejiang can try to constrain and assess the ecological environmental protection tasks of each city with higher environmental quality standards.

Due to data limitations, this study only predicted $PM_{2.5}$ concentration changes in the context of medium and long-term socioeconomic planning, represented by 11 cities in Zhejiang Province in key regions. For future research, the study can continue to expand the sample of cities and conduct detailed prediction model construction around the population size and industrial characteristics of different cities. And the scenario index settings can be improved on the basis of clarifying the energy consumption and $PM_{2.5}$ emission coefficients of different industry sectors. Therefore, it can increase the accuracy of $PM_{2.5}$ forecast and provide a scientific foundation and suggestions for medium- and long-term environmental planning.

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Declarations

Conflicts of interest The authors declare no conflict of interest.

Consent to participate Not applicable (This study does not contain any individual person's data in any form).

Consent to publish Not applicable (This study does not contain any individual person's data in any form).

Ethical approval Ethical approval was not required for secondary analysis of anonymous data.

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