Journal of Environmental Management 295 (2021) 113051

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Impacts of haze pollution on China's tourism industry: A system of economic loss analysis

Yan Hao [a], Xinsong Niu [b,*], Jianzhou Wang [c]

[a] Business School, Shandong Normal University, Jinan, 250014, China
[b] School of Statistics, Dongbei University of Finance and Economics, Dalian, 116025, China
[c] Macau Institute of Systems Engineering, Macau University of Science and Technology, Macau, 999078, China

ARTICLE INFO

Keywords:
Haze pollution
Optimal distribution
Economic loss
Optimization algorithm

ABSTRACT

Haze pollution not only negatively influences public health but also causes great economic losses. However, most previous studies have mainly focused on health-related economic losses, while the negative effects of haze pollution on the tourism industry are often ignored, leading to the unsustainable development of tourism. In this context, contrasting with previous research perspectives, this article selected several representative tourist cities from East China, South China, Central China, North China, Northwest China, Southwest China, and Northeast China as research objects in an empirical study, developing an economic loss analysis system to quantitatively evaluate the losses in the tourism industry caused by haze pollution. This system uses the satin bower bird optimization-based distribution estimation method to identify the optimal distribution of haze pollution, demonstrating superior performance to the traditional estimation method. Meanwhile, the optimal distribution of haze pollution is employed to measure the probability of different concentration limits in each area. Furthermore, the economic loss formula of the tourism industry is proposed in the devised system, calculating the economic loss caused by haze pollution at different degrees. The results show that haze pollution in different degrees has caused varying degrees of losses to China's tourism industry. In terms of seasonality and regionality, different seasons and different regions produce different results. Compared with summer, autumn and winter haze pollution is more severe, creating obvious seasonal differences. There is also a regional agglomeration effect, whereby the regional distribution of haze pollution is consistent with each region's economic development.

1. Introduction

Air pollution is a major problem on a global scale, affecting human health and well-being (Jun et al., 2019; Wang et al., 2020d). One of the main pollutants is particulate matter with an aerodynamic diameter of less than 2.5 μm ($PM_{2.5}$) (Li et al., 2019). Excessive $PM_{2.5}$ content adversely affects human health, the ecosystem, and sustainable economic development (Wang et al., 2020a). The United States set the $PM_{2.5}$ standard in 1997 and its Environmental Protection Agency (EPA) revised the standard in 2006 (Caiazzo et al., 2013). In 2011, China began to use gravimetric analysis to measure PM_{10} and $PM_{2.5}$ in ambient air. This is the first time that the measurement of $PM_{2.5}$ was standardized (Wang et al., 2020c). The Chinese government is gradually paying more attention to smog pollution. Since the large-scale outbreak of haze in 2013, China's air quality has continued to deteriorate (Wang et al., 2018). The Travel & Tourism Competitiveness Report 2017 forum explained that of the 136 countries and economies that participated in its evaluation, China ranked first in the $PM_{2.5}$ concentration of haze pollution and lowest in the tourism environment and tourism environmental sustainability. According to data released by the China Meteorological Administration, 2013 was the most severe year since 1961 in the average number of days China's haze pollution appeared, leading to frequent flight delays, closures of scenic spots, and a high incidence of respiratory infections (Yang et al., 2020). Severe haze pollution negatively impacts the climate, environment, and every walk of life that is highly valued by people. However, it is generally believed that agriculture, transportation, and other industries are more vulnerable to impacts on the ecological environment and climate conditions—the sensitivity of tourism to shifting ecological environment and climate conditions is ignored. As one of China's pillar industries, tourism plays

* Corresponding author. School of Statistics, Dongbei University of Finance and Economics, Dalian, 116025, China.
E-mail address: xinsongniu@126.com (X. Niu).

https://doi.org/10.1016/j.jenvman.2021.113051
Received 15 November 2020; Received in revised form 5 June 2021; Accepted 7 June 2021
Available online 25 June 2021

an important role in transforming its economic structure, increasing the gross national product, and expanding employment. Although the issue of haze pollution's impact on the tourism industry has received extensive attention from relevant departments, including government departments and regulatory agencies, to date there are no specific research conclusions.

Rapidly developing after World War II, the tourism industry has consistently been considered both a sunrise industry and an environmental protection industry. China also has a large population and rich tourism resources, providing its tourism industry with huge development potential. However, tourism is mainly based on outdoor activities; therefore, the tourism industry is highly sensitive to climate, and the ecological environment and climatic conditions will directly affect its development (Qiang et al., 2020). For example, Sajjad et al. (2014) studied the causal relationship between air pollution and tourism development and found that air pollution and climate change negatively impact the development of tourism areas. Law and Cheung (2007) showed that poor air quality will reduce the satisfaction of tourists and affect the reputation of tourist destinations. Taking American National Forest Park as an example, Poudyal et al. (2013) pointed out that haze pollution reduces the number of tourists in scenic spots and affects their economic benefits. Haze pollution damages the image of tourist destinations, slows down the development of tourism, and reduces its economic benefits. Moreover, research by Gómez Martín (2005), Simpson and Siguaw (2008), Poudyal et al. (2013), and others on the impact of haze pollution on tourists' experience has demonstrated how haze pollution affects the viewing quality of scenic spots and tourists' overall experience. Relevant scholars have carried out a number of studies regarding the image problem of tourism destinations. Taking Beijing as a case study, Zhang et al. (2015) show that haze pollution greatly reduces the image of tourist scenic spots, affects tourists' travel decisions, and causes some tourists to abandon their travel plans. Haze pollution greatly reduces the beauty of scenic spots and diminishes the image of tourist spots.

Moreover, haze pollution affects the supply and demand of tourism, thereby affecting its economic benefits and seriously hindering further development. In other words, haze pollution has caused serious losses to the tourism industry. In 2013, affected by haze pollution, the number of inbound tourists received by Beijing was 4.501 million, and the foreign exchange income of inbound tourism was 4.795 billion USD. The number of inbound tourists and the foreign exchange of inbound tourism revenue had decreased by 10.1% and 6.9% year by year. However, although many scholars believe that haze pollution has serious and negative impacts on the tourism industry, few have estimated the economic losses caused by haze pollution within it. For example, Anaman and Looi (2000) studied the negative impact of smog activities in Brunei on the local tourism industry. The study found that the number of tourists during severely polluted months was significantly lower than in months without air pollution and believed that the haze generated direct economic losses in the local tourism industry.

Accordingly, an economic loss analysis system based on the optimal distribution function of haze pollution is proposed to quantify the economic loss in the tourism industry, starting from the optimal distribution strategy. The distribution type of haze pollutant concentration is affected by many factors. For example, when regions or pollutants are different, the statistical distribution of haze varies (Jiang et al., 2019). Existing studies have used probability density functions to describe the distribution of pollutant concentrations and to determine the dispersal of pollutants, including Normal distribution and Gamma distribution. Commonly used calculation methods include the graphical method, the least square method, and maximum likelihood estimation (Jiang et al., 2017). Although these methods are relatively simple in principle, their calculation accuracy is easily affected by subjective factors, resulting in relatively poor accuracy. With the rapid development of artificial intelligence (AI) technology, an increasing number of AI optimization algorithms have been applied (Liu et al., 2021; Guan et al., 2019). Compared with traditional statistical methods, AI technology has obvious advantages (Wang et al., 2020b; Tian and Hao, 2019). Therefore, we constructed a pollutant distribution assessment of major tourist cities based on intelligent optimization. To obtain the optimal statistical distribution of haze pollution, this paper selects $PM_{2.5}$ as the research object and uses AI optimization algorithms to determine the optimal distribution function of $PM_{2.5}$ and identify the corresponding probability of different $PM_{2.5}$ concentration limits. Then, we analyze suggestions for people's activities under different air quality standards and quantify the impact of different pollution levels on the tourism industry. The main process framework of this article is shown in Fig. 1.

Compared with existing research methods in the literature, the innovation and novelty of this article are as follows：

(1) **An artificial intelligence optimization algorithm was used to evaluate the optimal distribution function of the main pollutant of haze.** The AI optimization algorithm generates more accurate model parameters for relevant haze pollutant data, which is an important factor in evaluating the economic loss haze pollution causes in the tourism industry.
(2) **Establish a loss assessment system to quantify the economic loss of the tourism industry caused by haze pollution.** Based on the optimal distribution of haze pollution, this paper designs a theoretical framework for measuring the economic loss of haze pollution to the tourism industry and expands the research on the evaluation of the economic loss of the tourism industry caused by haze pollution.
(3) **Quantify the economic loss of haze pollution in China's tourism industry.** Fourteen important tourist cities in China's seven geographical regions (Northeast China, East China, North China, Central China, South China, Southwest China, and Northwest China) were selected as the research samples, and the loss assessment system established in this paper was used to calculate the economic losses caused by haze pollution within China's tourism industry. The results show that haze pollution has caused huge economic losses in China's tourism industry.
(4) **The construction of an economic loss analysis system provides a new method to evaluate and analyze the economic loss of haze pollution.** The economic loss evaluation system constructed in this paper can effectively evaluate the economic loss caused by haze pollution in the tourism industry and provide guidance and support for the tourism industry's healthy development. In addition, it can function as a theoretical reference for evaluating other economic losses.

2. Process of constructing the economic loss analysis system

Pollutant concentration data can be used to evaluate air quality in tourist areas and as an effective basis for pollutant control. The statistical distribution function of haze pollution can quantify the corresponding probability of different haze pollutant concentration limits. The probability of occurrence under different levels of haze pollution can be obtained, and the economic losses caused to the tourism industry can be measured according to the harm caused by different haze pollution conditions. Therefore, to evaluate the economic loss caused by haze pollution in the tourism industry, this study designs an economic loss analysis system based on the optimal distribution function of haze pollution.

2.1. *Evaluation strategy for the statistical distribution of haze pollutant concentrations*

To determine the best distribution function of $PM_{2.5}$ pollutants, we used four commonly used distribution functions: Weibull distribution, Gamma distribution, Rayleigh distribution, and Lognormal distribution. There are many methods for estimating the parameters of a distribution

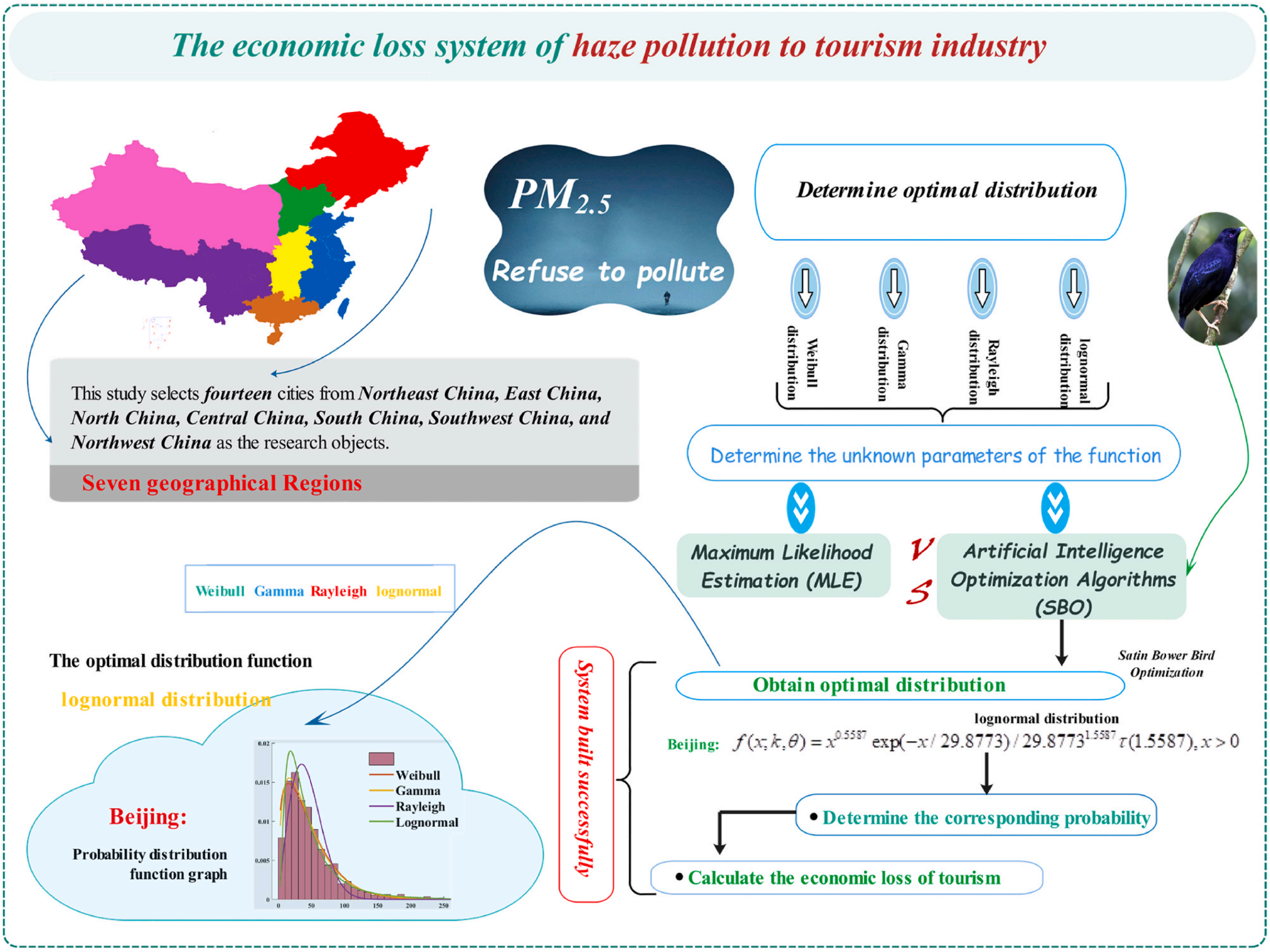

Fig. 1. The main framework of this paper.

function. In this paper, when determining the method of unknown parameters in our distribution function, we chose two methods for comparison (traditional maximum likelihood estimation (MLE) and artificial intelligence optimization algorithms (SBO)), identifying the pros and cons of the two methods via the fitness evaluation index $\boldsymbol{R^2}$.

(1) Maximum likelihood estimation (MLE)

Maximum likelihood estimation is a parameter estimation, and its theoretical basis is the principle of maximum likelihood. The introduction to MLE is as follows:

Let $f(x_i, \theta)$ be the probability density function of a certain time series, and then use the maximum likelihood estimation method to estimate the parameterθ.

Construct the likelihood function: $L(\theta) = L(x_1, x_2, \ldots, x_n; \theta) = \prod_{i=1}^{n} f(x_i, \theta)$, θ is the parameter to be estimated, and $\boldsymbol{x_i}$ is the ***i-th*** observation value of the sample.

Logarithmically process the likelihood function to obtain $\ln L(\theta)$. If there is a value of $\widehat{\theta}$ that satisfies the following formula: $L(x_1, x_2, \ldots, x_n; \widehat{\theta}) = \max \prod_{i=1}^{n} f(x_i, \theta)$, then $\widehat{\theta}$is the maximum likelihood estimate of θ. Because the extreme points of $L(\theta)$and $\ln L(\theta)$are the same, perform derivative processing on$\ln L(\theta)$:$\frac{d}{d\theta} \ln L(\theta) = 0$. Solve the likelihood equations to obtain the optimal parameter estimates $\widehat{\theta}$.

(2) Artificial intelligence optimization algorithm

In recent years, many new swarm intelligence algorithms have emerged (Hao and Tian, 2020; Hao et al., 2020). The Satin Bower Bird Optimization algorithm (SBO) is a new type of meta-heuristic optimization algorithm proposed by Moosavi et al. (Samareh Moosavi and Khatibi Bardsiri, 2017). It combines operations such as dynamic step size and mutation. The algorithm has good search performance and has been successfully applied in many fields. Therefore, the SBO algorithm is chosen to optimize the parameters of the distribution function and determine the optimal distribution function of haze pollution.

According to the living habits of satin blue gardener birds, the main process of the SBO algorithm is as follows:

An initial population containing $\boldsymbol{N}$ individuals is randomly generated, the variable to be optimized is ***D-dimensional***, and the current evolutionary algebra is $\boldsymbol{t}$.

Calculate the fitness value of each individual $\boldsymbol{fit_i}$.

$$P = \frac{fit_i}{\sum_{i=1}^{N} fit_n}, fit_i = \begin{cases} \frac{1}{1 + f(x_i)}, & f(x_i) \geq 0 \\ 1 + |f(x_i)|, & f(x_i) < 0 \end{cases} \tag{1}$$

$f(x_i)$ is the cost function of the ***i-th*** individual. The ***cost function*** is the ***objective function***, and each iteration ensures that the value of the ***objective function*** keeps decreasing.

$$\textit{Location update}: x_{ik}^{t+1} = x_{ik}^{t} + \lambda_k \left(\left(\frac{x_{jk} + x_{elite,k}}{2} \right) - x_{ik}^{t} \right) \tag{2}$$

where x_{ik}^{t+1} is the ***k-th component*** of the ***i-th individual*** of the ***t+1-generation***, $x_{jk}$is the ***k-th dimension*** component of the currently obtained optimal position, j is determined by the roulette mechanism, $x_{elite,k}$ is the current optimum of the entire population position, $\lambda_k = \frac{\alpha}{1+p_j}$ is the step length factor (α is the maximum step size, and $p_j$is the probability of the target courtship pavilion being selected).

Mutations: At the end of each cycle of each algorithm, there is a probability that random mutation will occur, and x_{ik}obeys the normal distribution:

$$\begin{aligned} & x_{ik}^{t+1} \sim N\left(x_{ik}^{t}, \sigma^2\right) \\ & N\left(x_{ik}^{t}, \sigma^2\right) = x_{ik}^{t} + (\sigma^* N(0,1)) \\ & \sigma = z^*(\mathrm{var}_{\max} - \mathrm{var}_{\min}) \end{aligned} \tag{3}$$

Where z is the scaling factor.

Combine the old population and the population obtained from the mutation, evaluate the function value of each individual, and keep the individual with the smallest function value.

$$P_{excellent} = \int_0^{35} f(x)dx \tag{4}$$

$$P_{good} = \int_{35}^{75} f(x)dx \tag{5}$$

$$P_{light\ pollution} = \int_{75}^{115} f(x)dx \tag{6}$$

$$P_{moderate\ pollution} = \int_{115}^{150} f(x)dx \tag{7}$$

$$P_{heavy\ pollution} = \int_{150}^{250} f(x)dx \tag{8}$$

$$P_{severe\ pollution} = \int_{250}^{\infty} f(x)dx \tag{9}$$

2.2. *Economic loss evaluation systematic theoretical framework*

Based on the optimal distribution of haze pollution, this paper designs an evaluation system to measure the economic loss of haze pollution in the tourism industry. The main theoretical framework of the system is designed as follows:

(1) Evaluation of the optimal distribution function of haze pollution. To obtain the optimal statistical distribution of haze pollution, this paper selects $PM_{2.5}$ as the research object and uses artificial intelligence optimization algorithms to determine the optimal distribution function *f(x)* of haze pollution $PM_{2.5}$.

(2) Determine the corresponding probability of different $PM_{2.5}$ concentration limits in the study area. Air quality includes six levels, which correspond to the six limits of $PM_{2.5}$ concentration, as shown in Table 1(Sheng et al., 2015; Liu et al., 2020). According to the optimal distribution function *f*(*x*) of $PM_{2.5}$, the corresponding probabilities of different air quality standards in various regions—*excellent, good, light pollution, moderate pollution, heavy pollution, and serious pollution*—can be obtained.

(3) Calculate the economic loss of tourism under different pollution levels. Table 1 gives suggestions for people's activities under different air quality standards. Specifically, when the air quality standard is *excellent,* all people can travel normally. In other words, smog pollution does not cause economic losses to the tourism industry. When the air quality standard is *good*, it is recommended that a small number of sensitive people reduce outdoor activities. Simply put, when the air quality is *good*, it can be regarded as haze pollution that does not cause economic losses to the tourism industry. When the air quality is *light pollution*, the elderly, children, and patients with respiratory diseases should reduce outdoor activities. Considering the susceptibility of older adults to respiratory disease and the availability of data, we hypothesize that haze pollution only affects the tourism industry by affecting the travel of the elderly and children when the air quality is *light pollution*. Similarly, when the air quality is *moderate pollution*, this article suggests that haze pollution impacts the elderly and children. In addition, when the air quality is *heavy pollution or serious pollution*, the general population should avoid outdoor exercise. Therefore, it follows that when the air quality is *heavy pollution or serious pollution*, haze pollution affects the tourism industry by preventing all people from going outside. In sum, when the air quality is *light pollution, moderate pollution, heavy pollution, and serious pollution*, haze pollution causes economic losses in the tourism industry. Defining the domestic tourism income of a certain area as Y_1, the domestic tourism economic loss caused by haze pollution within the tourism industry is:

$$S_{light\ pollution} = Y_1 / \left(1 - P_{light\ pollution} * P_{elderly+children}\right) - Y_1 \tag{10}$$

$$S_{moderate\ pollution} = Y_1 / \left(1 - P_{moderate\ pollution} * P_{elderly+children}\right) - Y_1 \tag{11}$$

$$S_{heavy\ pollution} = Y_1 / \left(1 - P_{heavy\ pollution}\right) - Y_1 \tag{12}$$

$$S_{severe\ pollution} = Y_1 / \left(1 - P_{severe\ pollution}\right) - Y_1 \tag{13}$$

$$S = S_{light\ pollution} + S_{moderate\ pollution} + S_{heavy\ pollution} + S_{severe\ pollution} \tag{14}$$

$P_{elderly+children}$is the sum of the proportions of the elderly and children in a certain year in China. $S_{light\ pollution}$, $S_{moderate\ pollution}$, $S_{heavy\ pollution}$, and $S_{severe\ pollution}$are the losses caused to the domestic tourism industry when the air quality standards are *light pollution, moderate pollution, heavy pollution, and serious pollution*, respectively, and $S$is the total loss caused by haze pollution in domestic tourism income.

We define the tourism foreign exchange income of a certain area as Y_2, and the loss of tourism foreign exchange income caused by haze pollution to the tourism industry is:

$$Q_{light\ pollution} = Y_2 \Big/ \left(1 - P_{light\ pollution} * P'_{elderly+children}\right) - Y_2 \tag{15}$$

$$Q_{moderate\ pollution} = Y_2 \Big/ \left(1 - P_{moderate\ pollution} * P'_{elderly+children}\right) - Y_2 \tag{16}$$

Table 1
$PM_{2.5}$ level and activity recommendations.

Air quality	$PM_{2.5}$ concentration (ug/m^3)	Activity recommendations
excellent	0–35	Everyone can exercise normally outdoors
good	35–75	A small number of sensitive people reduce outdoor activities
light pollution	75–115	Elderly, children, and patients with respiratory diseases reduce outdoor activities
moderate pollution	115–150	Elderly, children, and patients with respiratory diseases should avoid outdoor activities
heavy pollution	150–250	The elderly, children, and patients with lung diseases should stop outdoor activities, and the general population should reduce time outdoors
serious pollution	>250	The elderly, children, and patients should only be active indoors, and the general population should avoid outdoor activities

$$Q_{heavy\ pollution} = Y_2 / \left(1 - P_{heavy\ pollution}\right) - Y_2 \quad (17)$$

$$Q_{severe\ pollution} = Y_2 / \left(1 - P_{severe\ pollution}\right) - Y_2 \quad (18)$$

$$Q = Q_{light\ pollution} + Q_{moderate\ pollution} + Q_{heavy\ pollution} + Q_{severe\ pollution} \quad (19)$$

where $P'_{elderly+children}$ represents the proportion of the elderly and children in a certain year abroad; $Q_{light\ pollution}$, $Q_{moderate\ pollution}$, $Q_{heavy\ pollution}$, and $Q_{severe\ pollution}$ are the tourism foreign exchange income when the air quality standards are *light pollution, moderate pollution, heavy pollution, and severe pollution*, respectively, and Q is the total loss caused by pollution in foreign exchange income from tourism.

3. Study area

China's regional and large-scale haze pollution mainly occurs within three major urban agglomerations in the Yangtze River Delta, the Pearl River Delta, and the Beijing-Tianjin-Hebei, and the central Liaoning urban agglomeration, the Changzhutan urban agglomeration, and the Chengdu-Chongqing Economic Zone. In these regions, the density of cities is high, energy consumption is concentrated, and the tourism industry is relatively developed, comprising a large proportion of China's tourism output. Affected by the spread and transportation of pollution due to weather conditions, the air pollution in small- and medium-sized cities around metropolitan areas has become increasingly serious, causing mounting economic losses.

China is generally divided into seven geographic regions. To evaluate the economic loss of haze to China's tourism industry, this study selects *fourteen* cities from *Northeast China, East China, North China, Central China, South China, Southwest China, and Northwest China* as its research objects. The detailed geographic location labeling of the selected 14 major tourist cities in China's seven regions is shown in Fig. 2.

4. Evaluation results of haze pollution distribution in tourist cities

The distribution function has been widely used in many specific research fields. For example, Sun et al. (2013) used Gaussian, Logarithmic normal (Lognormal), Gamma, and generalized extreme value distributions to simulate the distribution function of $PM_{2.5}$; Song et al. (2015) selected the Weibull distribution, Rayleigh distribution, Lognormal distribution, and Gamma distribution to evaluate the distribution function of PM pollutants. Therefore, given the $PM_{2.5}$ pollutant concentration x, this study employs four commonly used air quality distribution functions (Xu et al., 2017)—Weibull, Gamma, Rayleigh, and Lognormal distributions—to fit the observation data of haze pollution in typical tourist cities. The probability density functions of the four distribution functions are shown in Table 2.

Fig. 2. The distribution of seven geographical regions in China.

Table 2
Probability density function of haze pollutant concentration distribution.

Distribution type	Probability density function	Statistical parameters
Weibull distribution	$f(x;\lambda,k) = k/\lambda(x/\lambda)^{k-1}\exp[-(x/\lambda)^k],$ $x \geq 0$	Scale : $\lambda > 0$ Shape : $k > 0$
Gamma distribution	$f(x;k,\theta) = x^{k-1}\exp(-x/\theta)/\theta^k\tau(k),$ $x > 0$	Scale : $\theta > 0$ Shape : $k > 0$
Rayleigh distribution	$f(x;\sigma) = x/\sigma^2\exp(-x^2/2\sigma^2), x \geq 0$	Scale : $\sigma > 0$
Lognormal distribution	$f(x;\mu,\sigma) = 1/x\sigma\sqrt{2\pi}\exp(-(\ln x-\mu)^2/2\sigma^2), x > 0$	Scale : $\sigma > 0$ Location : $\mu > 0$

4.1. Description of statistical characteristics

This study comprehensively considers factors such as the number of inbound tourists and geographical distribution, selecting 14 cities from the seven geographic regions of China (***Northeast China, East China, North China, Central China, South China, Southwest China, and Northwest China***) as the study object (a total of 14 key tourist cities: ***Harbin, Dalian, Jinan, Hangzhou, Beijing, Shijiazhuang, Zhengzhou, Wuhan, Guangzhou, Haikou, Chengdu, Chongqing, Urumchi***, and ***Xi'an***).

Compared with other regions, the average concentration of $PM_{2.5}$ in North China, East China, Northwest China, and Central China is relatively higher, and the air quality is worse than in South China. Within North China, Shijiazhuang City has the highest average concentration of $PM_{2.5}$, reaching 71.2676 μg/m^3. Jinan City is located in North China, where the average concentration of $PM_{2.5}$ has reached 56.2584 μg/m3. The average concentration of $PM_{2.5}$ in Xi'an, located in Central China, reached 60.9224 μg/m^3, and its highest daily average concentration reached an astonishing 493 μg/m^3. The detailed data is shown in Table 3.

4.2. Result of the optimal distribution function

To obtain the optimal distribution function of $PM_{2.5}$ pollutants in each tourist city and better understand the characteristics of the relevant pollutant concentration, we use four distribution functions: Weibull distribution, Gamma distribution, Rayleigh distribution, and Lognormal distribution modeling of the $PM_{2.5}$ data sequence. According to the fitness evaluation index $\boldsymbol{R^2}$, two evaluation methods—namely, maximum likelihood estimation (MLE) and the satin blue gardener bird (SBO) optimization algorithm—are applied to determine the distribution of pollutants. The larger the $\boldsymbol{R^2}$ value is, the better the fit between the cumulative probability of fitting and the cumulative probability of experience (Wang et al., 2015). Appendix A1 and Fig. 3 display the results of the distribution fitting. According to the $\boldsymbol{R^2}$ value, the MLE and SBO strategies have achieved good fitting results, while the satin blue gardener bird optimization algorithm is effective for haze pollution. The degree of fit $\boldsymbol{R^2}$ of the concentration distribution function is greater than that of the MLE, indicating that SBO has good fitting performance. Taking Beijing as an example, the $\boldsymbol{R^2}$ of SBO for the four distribution functions are 0.9983, 0.9991, 0.9554, and 0.9977, which are 0.0047, 0.0051, 0.1128, and 0.0003 higher than the $\boldsymbol{R^2}$ value estimated by MLE. This shows that the artificial intelligence optimization algorithm based on the SBO algorithm has a good fitting effect. According to the degree of fit $\boldsymbol{R^2}$ of different distribution functions of each city, the optimal distribution function of $PM_{2.5}$ in different tourist cities varies; the optimal distribution function of Beijing $PM_{2.5}$ is the gamma distribution and the optimal distribution function of Shijiazhuang $PM_{2.5}$ is the lognormal distribution function. Meanwhile, Appendix A2 shows the distribution parameters, and Appendix A3 lists the estimated values of the distribution parameters based on the MLE and SBO methods. According to the estimated values of the distribution parameters obtained by the SBO method, the specific distribution functions of the $PM_{2.5}$ series of haze pollution in Beijing and Shijiazhuang can be obtained as shown in Eqs. (20) and (21):

$$f(x;k,\theta) = x^{0.5587}\exp(-x/29.8773)/\left(29.8773^{1.5587}\tau(1.5587)\right), x > 0 \quad (20)$$

$$f(x;\mu,\sigma) = \frac{1}{x^*0.7345^*\sqrt{2\pi}}\exp\left(-(\ln x - 3.9878)^2/2*0.7345^2\right), x > 0 \quad (21)$$

In East China, taking Hangzhou as an example, the $\boldsymbol{R^2}$ values of the SBO algorithm for the four distribution functions are 0.9942, 0.9997, 0.9933, and 0.9999, which are 0.0059, 0.0026, 0.0146, and 0.0004 higher than the $\boldsymbol{R^2}$ values estimated by MLE, respectively. According to the maximum $\boldsymbol{R^2}$ values of the different distribution functions of Hangzhou and Jinan, the best fitting distribution functions of Hangzhou and Jinan $PM_{2.5}$ are lognormal distribution functions. In addition, Appendix A3 shares the parameter estimates based on the MLE and SBO methods. According to the best fitting distribution function of each city and the distribution parameter estimated values obtained by the SBO method, the specific $PM_{2.5}$ series of Hangzhou and Jinan's distribution function formulas, as shown in Eqs. (22) and (23):

$$f(x;\mu,\sigma) = \frac{1}{x^*0.5772^*\sqrt{2\pi}}\exp\left(-(\ln x - 3.5157)^2/2*0.5772^2\right), x > 0 \quad (22)$$

$$f(x;\mu,\sigma) = \frac{1}{x^*0.5940^*\sqrt{2\pi}}\exp\left(-(\ln x - 3.8390)^2/2*0.5940^2\right), x > 0 \quad (23)$$

Table 3
Basic statistical characteristics of PM2.5 observation data.

Geographical area	Selected city	Mean	Maximum	Standard deviation	skewness	kurtosis
Northeast	Harbin	45.8694	455	51.5501	3.2056	17.2808
	Dalian	32.4511	243	26.3482	2.7059	13.8386
East China	Jinan	56.2584	289	39.0679	2.1845	9.9718
	Hangzhou	40.1178	186	24.2214	1.6640	6.7851
North China	Beijing	48.8155	454	43.9571	2.7697	16.6140
	Shijiazhuang	71.2676	445	59.9219	2.1687	8.7951
Central China	Zhengzhou	56.6584	355	50.6442	2.1791	9.0942
	Wuhan	47.2192	223	31.0032	1.5912	6.4003
South China	Guangzhou	32.6037	155	18.3643	1.6780	7.9073
	Haikou	18.0228	73	10.7490	1.6387	6.2806
Southwest	Chengdu	47.3607	313	35.7815	2.1052	10.0325
	Chongqing	39.5680	171	25.5809	1.9035	7.4035
Northwest	Urumchi	55.8895	360	59.6294	1.8728	6.4779
	Xi'an	60.9224	493	57.4297	2.5739	12.5090

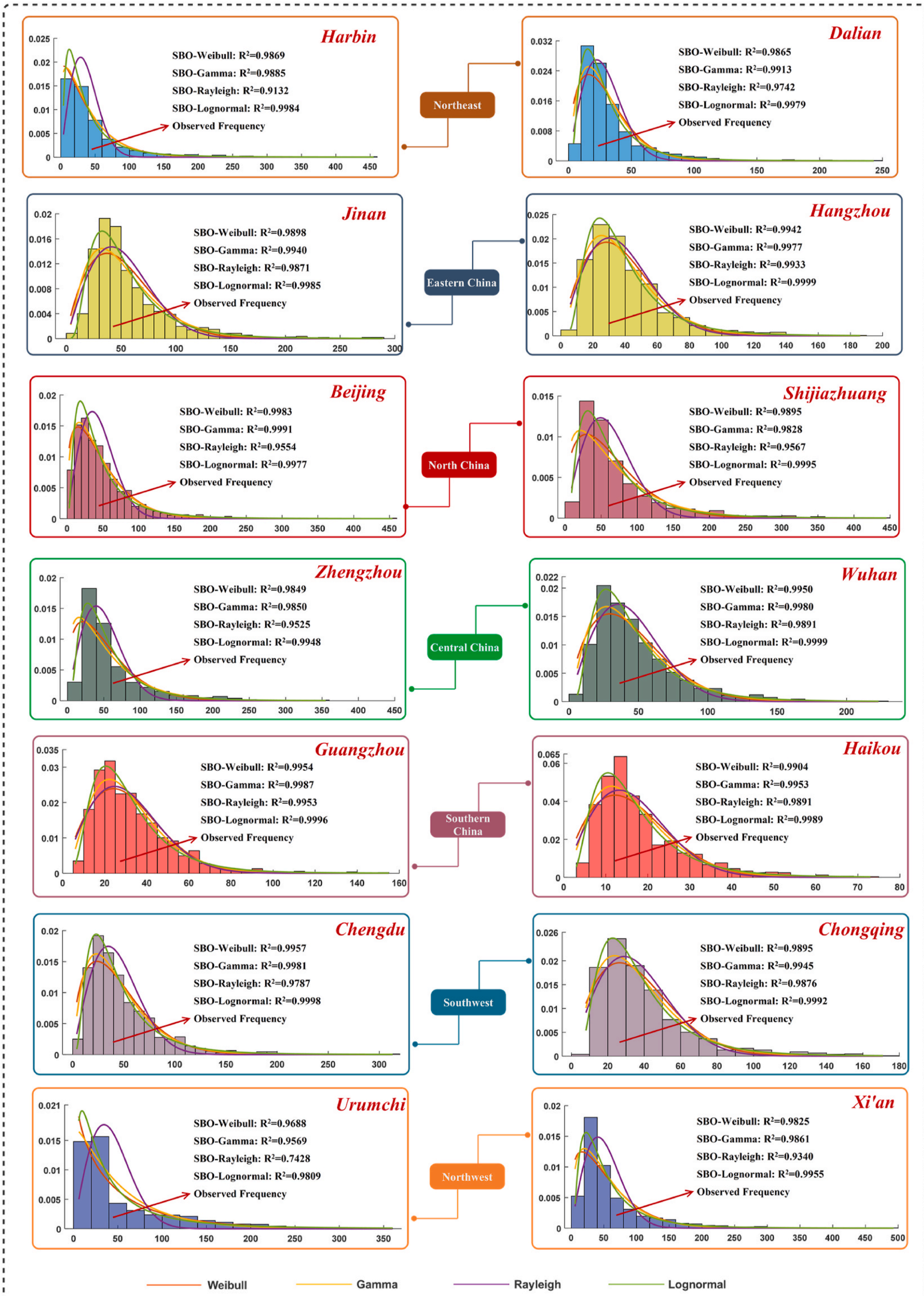

Fig. 3. The sequences and probability density functions of several distributions.

5. The loss caused by haze pollution in the tourism industry

Before evaluating the damage caused by haze pollution to the tourism industry, it is necessary to determine the probability of different $PM_{2.5}$ concentration limits within each region. According to the optimal distribution function of haze pollutant $PM_{2.5}$ obtained above, the corresponding probability under the limit of $PM_{2.5}$ concentration in different regions can be calculated, and the calculation results are shown in Appendix B1. Taking $PM_{2.5}$ concentration limit 0–35 as an example, the probability of Hangzhou in Central China is 0.5274, the probability of Guangzhou in South China is 0.6621, the probability of Wuhan in Central China is 0.4264, the probability of Beijing in North China is 0.4740, the probability of Xi'an in Northwest China is 0.3902, the probability of Chongqing in Southwest China is 0.5537, and the probability of Dalian in Northeast China is 0.6957. The corresponding probabilities of other $PM_{2.5}$ concentration limits in each region are detailed in Appendix B1.

Next, according to the economic loss formula of tourism under

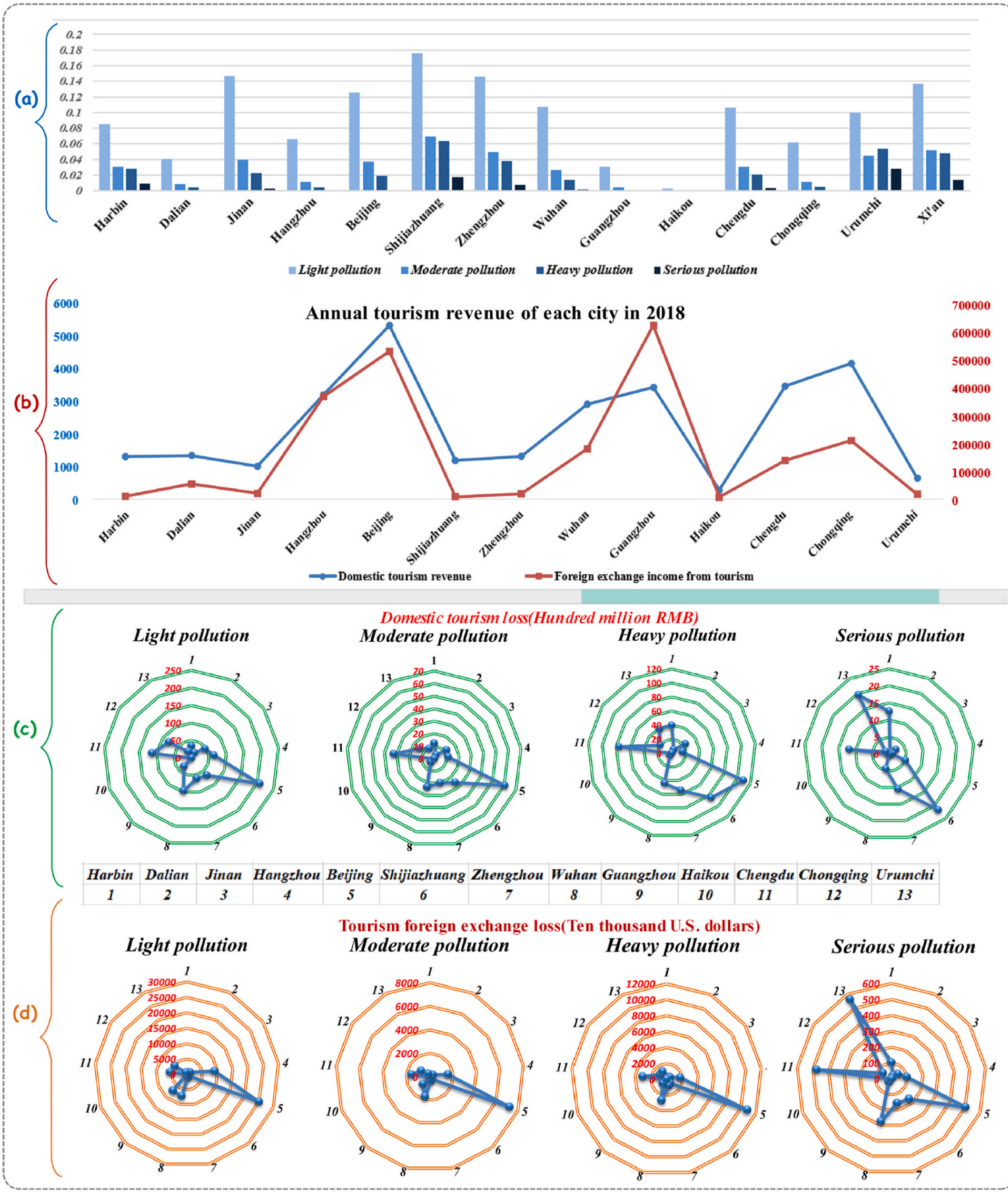

Fig. 4. (a) Shows the corresponding probability of different $PM_{2.5}$ concentration limits in various regions; **(b)** shows the annual tourism revenue of each city in 2018; **(c)** is the loss of domestic tourism revenue in each city during 2018; and **(d)** represents the loss of foreign exchange income from tourism in each city during 2018.

different pollution levels in Chapter 3, we can obtain the economic loss caused by haze pollution in each region.

To obtain the economic loss caused by haze pollution in China's tourism industry, the domestic tourism income and tourism foreign exchange income of 14 key tourist cities from 2017 to 2019 were selected as the research objects. A brief description of the data and a rough loss result are explained in Fig. 4, and more detailed results are discussed below. The data come from the annual statistical bulletins and statistical yearbooks of each tourist city. The total proportion of the elderly and children is the total population aged ***0–14*** and the population aged ***65*** and over in China from 2017 to 2019, via data from the National Bureau of Statistics. The total proportion of the elderly and children in foreign countries is the total world population aged ***0–14*** and the population aged ***65*** and over (the proportion of the elderly and children in 2019 is the average value of 2017 and 2018). These statistics come from the World Bank database. Significantly, the tourism data of Dalian and Wuhan in 2019 have not been released, so only the domestic tourism income and foreign exchange income from tourism in Dalian and Wuhan from 2017 to 2018 are selected as the research objects in this study. In addition, for Xi'an, only the total tourism revenue (the sum of domestic tourism revenue and foreign exchange income from tourism) data is released for tourism data. Therefore, the tourism revenue of Xi'an from 2017 to 2019 is selected as the research object, and the data originate in the statistical bulletins and statistical yearbooks of various years in Xi'an. The data on annual tourism revenue and the population age structure are displayed in Appendix B3, Appendix B4, and Appendix B5. The specific number of tourists in each city is shown in Appendix B2.

5.1. Analysis of the economic loss of haze pollution in the tourism industry

Appendices C1-C8 show the economic loss value caused by haze pollution in the tourism industry in 14 cities of the seven major regions.

In Northeast China, for Dalian, from 2017 to 2018, the losses caused by haze pollution in domestic tourism income were 22.9163 and 26.2810 hundred million RMB, respectively, and the losses caused by haze pollution foreign exchange income were 1191.9467 and 1239.0478 ten thousand USD, respectively. These accounted for 0.3112%, 0.3427% and 0.0104%, 0.0103% of GDP in the corresponding years. For Harbin, from 2017 to 2019, haze pollution caused economic losses of 83.4736, 98.7990, and 113.0492 hundred million RMB in its domestic tourism income, accounting for 1.3135%, 1.5681%, and 2.1537% of GDP, respectively, as well as losses of 1068.5499, 886.3142, and 2726.3539 ten thousand USD in tourism foreign exchange income, respectively.

East China, taking Jinan and Hangzhou in East China as the research objects, the economic loss of these two cities under the haze pollution was evaluated and studied. Appendix C2 shows the economic loss of the tourism industry caused by haze pollution in Hangzhou and Jinan. It can be seen that haze pollution has caused serious losses to both Hangzhou and Jinan. From the perspective of the total loss of tourism economy, Hangzhou's loss of foreign exchange income from tourism from 2017 to 2018 far exceeded that of Jinan. Although the air quality management level of Hangzhou far exceeds that of Jinan, its annual foreign exchange income from tourism far exceeds that of Jinan. Specifically, the losses caused by haze pollution to Jinan City and Hangzhou City's tourism foreign exchange earnings losing from 2017 to 2018 were: 1916.5159, 2053.2590 ten thousand USD and 11393.0844, 12343.2121 ten thousand USD, separately, accounting for 0.0170%, 0.0167% and 0.0579%, 0.0585% of their respective cities' GDP.

Appendix C3 displays the economic loss in the tourism industry caused by haze pollution in Beijing and Shijiazhuang. For Beijing, from 2017 to 2019, haze pollution caused losses of 347.0250, 382.2633, and 409.2323 hundred million RMB in its domestic tourism revenue, accounting for 1.1613%, 1.1547%, and 1.1546% of its GDP, respectively. Beijing's losses in tourism foreign exchange revenue were 40379.3650, 43619.0386, and 41013.4956 ten thousand USD, respectively. Regarding Shijiazhuang, from 2017 to 2019, haze pollution caused losses of 155.3773, 197.6761, and 236.0014 hundred million RMB in its domestic tourism revenue, accounting for 2.4049%, 3.2499%, and 4.0620% of its GDP, respectively. Shijiazhuang's losses in tourism foreign exchange income were 1650.4251 and 1696.2057 and 1839.2190 ten thousand USD, respectively. Of the 14 cities in the seven regions studied, Beijing and Shijiazhuang suffered the highest economic losses.

In Central China, for Zhengzhou City, from 2017 to 2019, light haze pollution caused losses of 50.8248, 60.4205, and 71.0526 hundred million RMB, respectively. Moderate haze pollution caused losses of 16.7092, 19.8515, and 23.3314 hundred million RMB; heavy haze pollution caused losses of 46.6253, 54.2013, and 62.4816 hundred million RMB. Finally, serious haze pollution brought losses of 9.0377, 10.5062, and 12.1112 hundred million RMB, respectively. The losses caused by light haze pollution are the most serious, accounting for 0.5567%, 0.5957%, and 0.6131% of Zhengzhou's GDP, respectively. From 2017 to 2018, haze pollution heavily impacted Wuhan's domestic tourism revenue and tourism foreign exchange revenue. Losses of 147.6335 and 168.8019 hundred million RMB occurred within its domestic tourism income, accounting for 1.1009% and 1.1369% of Wuhan's GDP, respectively. Losses of 10800.1165 and 12035.8541 ten thousand USD occurred in foreign exchange income from tourism, respectively.

To assess the economic loss of haze pollution in the tourism industry of South China, Guangzhou and Haikou were selected as the research objects. For Guangzhou, from 2017 to 2019, haze pollution had a greater impact on foreign exchange income from tourism, causing losses of 8372.5706, 8615.5701, and 8669.1814 ten thousand USD to foreign exchange income from tourism. These accounted for 0.0249%, 0.0241%, and 0.0235% of Guangzhou's GDP, respectively. Haikou's air quality is better than other areas, and haze pollution causes less damage to its tourism industry. In general, from 2017 to 2019, haze pollution caused losses of 0.1989, 0.2267, and 0.2475 hundred million RMB in Haikou's domestic tourism revenue, respectively. The damage caused losses in its tourism foreign exchange revenue of 5.4842, 7.5855, and 9.2489 ten thousand USD, respectively.

The economic losses of haze pollution to tourism in Chengdu and Chongqing are detailed in Appendix C6. From 2017 to 2019, haze pollution caused losses of 188.2850, 234.3231, and 298.5287 hundred million RMB in Chengdu's domestic tourism revenue, accounting for 1.3556%, 1.5273%, and 1.7547% of its GDP, respectively. It also caused losses of 9563.4725, 10632.0311, and 11915.3166 ten thousand USD in tourism foreign exchange revenue, accounting for 0.0441%, 0.0443%, and 0.0448% of Chengdu's GDP, respectively. For Chongqing, haze pollution caused a loss of 82.6188, 115.0032, and 150.2343 hundred million RMB in domestic tourism revenue, respectively, from 2017 to 2019, accounting for 0.4117%, 0.5327%, and 0.6364% of Chongqing's GDP. Its loss in foreign exchange income of tourism was 6013.7963, 6776.6924, and 6769.6729 ten thousand USD, respectively.

Urumqi and Xi'an are selected as research objects in the Northwest region. From 2017 to 2019, haze pollution caused 55.5233, 87.0095, and 145.1908 hundred million RMB of losses in Urumqi's domestic tourism revenue, accounting for 2.0236%, 2.8070%, and 4.2541% of its GDP, respectively. It also caused losses of 2456.1762, 2682.1089, and 1713.7070 ten thousand USD in foreign exchange tourism income, respectively. For Xi'an, from 2017 to 2019, haze pollution caused losses of 207.0250, 325.6466, and 402.6449 hundred million RMB in tourism revenue in Xi'an, accounting for 2.7715%, 3.9000%, and 4.3198% of its GDP, respectively.

5.2. Influence of seasonality in haze pollution on economic loss in the tourism industry

Compared with summer, haze pollution is more serious in fall and winter, especially in the northern areas in China, where the seasonal difference is clearer. This is because most northern areas of China need heating in late fall and winter, and China's heating is still dominated by the burning of coal, which is the main source of haze pollution. To measure the impact of the seasonality of haze pollution on the economic losses in the tourism industry, taking Beijing as an example, we use quarterly data to identify the difference in the impact of haze pollution on the tourism industry. Here, the first quarter through the fourth quarter approximate winter, spring, summer, and autumn, respectively. First, we evaluate the optimal distribution function of haze pollution in different quarters, and the quarterly distribution fitting results of Beijing are shown in Appendix D1. Based on Appendix D1, it is evident that the optimal distribution functions of haze pollution in different quarters vary, following Weibull distribution, Gamma distribution, Weibull distribution, and Gamma distribution, respectively. Based on the quarterly distribution fitting results and the economic loss assessment method proposed in this study, the quarterly economic losses caused by haze pollution are obtained, as shown in Appendix D2. Based on the results listed in Appendix D2, when compared with the second quarter and third quarter, the economic losses caused by haze pollution in the tourism industry are more serious during the first and fourth quarters. This indicates that when haze pollution is more serious in autumn and winter, so too are the economic losses in the tourism industry. Moreover, the economic loss in the tourism industry caused by haze pollution during the first quarter is the most serious because smog pollution is at its worst during winter in China. Therefore, we can reasonably conclude that the seasonal differences of haze pollution generate relative seasonal impacts on the economic losses in the tourism industry.

5.3. The analysis of regional heterogeneity

(1) There is a regional agglomeration effect: high-concentration areas are in the central and northern parts of the east, such as Henan, Jiangsu, and Shandong. The Beijing-Tianjin-Hebei and Yangtze River Delta are all heavily polluted areas. Although the haze pollution situation in Beijing and Shanghai has improved, they are still heavily polluted areas.

(2) It presents regional characteristics of low in the west and high in the east, mainly related to economic development and climatic conditions: the haze pollution in the east region is the most serious, while the situation in the central and west regions are better than in the east. The regional distribution difference of haze pollution matches the economic development in each region. In addition, Hainan, Heilongjiang, and other provinces and cities in the east and central regions have relatively low pollution levels that are inseparable from climatic conditions.

5.4. The analysis of practical significance in this research

With the gradual transformation of the tourism industry to "leisure vacation", the environment of tourist destinations, including weather conditions, has become an important consideration. Tourists attach great importance to the weather conditions, whereby the role of the environment in their travel decisions has become increasingly prominent. As a significant contributor to environmental pollution in recent years, haze pollution offers a new perspective for research on climate change and the tourism industry. At present, tourism is an indispensable part of people's daily lives and the tourism industry is one of the largest foreign exchange earning industries. Thus, environmental problems represented by smog pollution are a serious threat to the development of China's tourism industry. As an industry that can foster the development of other industries, tourism has a significantly positive role in China's industrial adjustment and its ongoing high-quality economic development. With the emergence of the global effects and awareness of climate change, the impact of the tourism industry on the high-quality development of the economy has become increasingly important. Evaluating the economic losses caused by China's tourism industry through haze pollution demonstrates the impact of haze pollution on the tourism industry and quantifies the related economic losses. This is critical research into how the tourism industry responds to haze pollution in China, with practical significance to the promotion and sound development of China's rapidly expanding and powerful tourism industry. Moreover, this research can help ordinary people intuitively understand the impact on and economic losses caused by haze pollution in the tourism industry. The government and relevant departments formulate haze pollution control policies to provide support and reference, which has important practical significance for facilitating the ongoing development of China's tourism industry and reducing any economic losses caused by haze pollution.

6. Conclusion

To calculate the economic losses caused by haze pollution in the tourism industry, based on the optimal distribution function of haze pollution, this study measures the economic losses caused in the tourism industry of China and constructs an economic loss analysis system. First, an artificial intelligence optimization algorithm is used to optimize the distribution function of the haze pollutant $PM_{2.5}$ in each region. Next, the corresponding probability of different $PM_{2.5}$ concentration limits in each region is calculated. The tourism economic loss formula is then used to evaluate the economic losses caused by different degrees of haze pollution in the tourism industry. Moreover, a total of 14 representative tourist cities were selected from the seven geographical regions of China as the research objects. The results of this study show that the concentration of $PM_{2.5}$ in light pollution, moderate pollution, heavy pollution and serious pollution has produced varying degrees of losses to the tourism industry of China. Take Beijing as an example, in 2019, light haze pollution, moderate haze pollution, heavy haze pollution and serious haze pollution caused 223.5560, 65.1302, 115.2030 and 5.3432 hundred million RMB, Accounting for 0.6307%, 0.1837%, 0.3250% and 0.0151% of Beijing's GDP in corresponding years, respectively. Caused 23518.8706, 6818.5966, 10202.8164 and 473.2120 ten thousand USD foreign exchange income losses, respectively, the total of foreign exchange income losses accounting for 0.0741% of Beijing's GDP in corresponding years.

With respect to seasons, compared with summer, haze pollution is more serious during autumn and winter, especially in northern China, where seasonal differences are more obvious. Given the seasonal difference in haze pollution, its impact on the economic losses in the tourism industry varies according to the season. Moreover, there is a regional agglomeration effect, whereby the regional distribution of haze pollution is consistent with the economic development in each region. In general, the economic loss analysis system established in this paper effectively quantifies the economic loss caused by haze pollution in the tourism industry in China, thereby providing guidance and support for the development of the tourism industry. Evaluating the economic losses caused by haze pollution in the tourism industry has important practical significance for improving air quality and promoting the healthy development of tourism. Furthermore, utilizing historical data drawn from the specified haze pollution periods, the proportion of tourists affected by haze is calculated, whereby the economic loss of haze pollution caused in the tourism industry is evaluated. This better reflects the impact of haze pollution on the tourism industry. Although this method is challenging due to the lack of available data, it can be used as a valuable direction for future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by Major Program of National Social Science Foundation of China (Grant No. 17ZDA093).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.113051.

Credit author statement

Yan Hao: Conceptualization, Methodology, Software, Formal analysis, Supervision. Xinsong Niu: Methodology, Software, Writing -

Original Draft, Data curation. Jianzhou Wang: Funding acquisition, Validation, Formal analysis, Data curation.

References

Anaman, K.A., Looi, C.N., 2000. Economic impact of haze-related air pollution on the tourism industry in Brunei Darussalam. Econ. Anal. Pol. 30, 133–143. https://doi.org/10.1016/S0313-5926(00)50016-2.

Caiazzo, F., Ashok, A., Waitz, I.A., Yim, S.H.L., Barrett, S.R.H., 2013. Air pollution and early deaths in the United States. Part I: quantifying the impact of major sectors in 2005. Atmos. Environ. 79, 198–208. https://doi.org/10.1016/j.atmosenv.2013.05.081.

Gómez Martín, M.B., 2005. Weather, climate and tourism: a geographical perspective. Ann. Tourism Res. 32, 571–591. https://doi.org/10.1016/j.annals.2004.08.004.

Guan, H., Zhao, A., Shi, G., 2019. Research on E-Commerce Precision Poverty Alleviation. Economic Science Press (In Chinese).

Hao, Y., Tian, C., 2020. A hybrid framework for carbon trading price forecasting: the role of multiple influence factor. J. Clean. Prod. 262, 120378. https://doi.org/10.1016/j.jclepro.2020.120378.

Hao, Y., Tian, C., Wu, C., 2020. Modelling of carbon price in two real carbon trading markets. J. Clean. Prod. 244 https://doi.org/10.1016/j.jclepro.2019.118556.

Jiang, H., Wang, J., Wu, J., Geng, W., 2017. Comparison of numerical methods and metaheuristic optimization algorithms for estimating parameters for wind energy potential assessment in low wind regions. Renew. Sustain. Energy Rev. https://doi.org/10.1016/j.rser.2016.11.241.

Jiang, P., Li, C., Li, R., Yang, H., 2019. An innovative hybrid air pollution early-warning system based on pollutants forecasting and Extenics evaluation. Knowl. Base Syst. 164, 174–192. https://doi.org/10.1016/j.knosys.2018.10.036.

Jun, M.A., Ding, Y., Cheng, J.C.P., Jiang, F., Wan, Z., 2019. A temporal-spatial interpolation and extrapolation method based on geographic long short-term memory neural. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.117729.

Law, R., Cheung, C., 2007. Air quality in Hong Kong: a study of the perception of international visitors. J. Sustain. Tourism 15, 390–401. https://doi.org/10.2167/jost637.0.

Li, H., Wang, J., Li, R., Lu, H., 2019. Novel analysis–forecast system based on multi-objective optimization for air quality index. J. Clean. Prod. 208, 1365–1383. https://doi.org/10.1016/j.jclepro.2018.10.129.

Liu, Y., Dong, J., Xu, X., Jiang, Y., 2020. PM2.5 mass concentration variation in urban residential buildings during heating season in severe cold region of China: a case study in Harbin. Sci. Total Environ. 722, 137945. https://doi.org/10.1016/j.scitotenv.2020.137945.

Liu, Z., Jiang, P., Wang, J., Zhang, L., 2021. Ensemble forecasting system for short-term wind speed forecasting based on optimal sub-model selection and multi-objective version of mayfly optimization algorithm. Expert Syst. Appl. 177, 114974. https://doi.org/10.1016/j.eswa.2021.114974.

Poudyal, N.C., Paudel, B., Green, G.T., 2013. Estimating the impact of impaired visibility on the demand for visits to national parks. In: Tourism Economics, pp. 433–452. https://doi.org/10.5367/te.2013.0204.

Qiang, M., Shen, M., Xie, H., 2020. Loss of tourism revenue induced by coastal environmental pollution: a length-of-stay perspective. J. Sustain. Tourism 28, 550–567. https://doi.org/10.1080/09669582.2019.1684931.

Sajjad, F., Noreen, U., Zaman, K., 2014. Climate change and air pollution jointly creating nightmare for tourism industry. Environ. Sci. Pollut. Res. 21, 12403–12418. https://doi.org/10.1007/s11356-014-3146-7.

Samareh Moosavi, S.H., Khatibi Bardsiri, V., 2017. Satin bowerbird optimizer: a new optimization algorithm to optimize ANFIS for software development effort estimation. Eng. Appl. Artif. Intell. 60, 1–15. https://doi.org/10.1016/j.engappai.2017.01.006.

Sheng, L., Lu, K., Ma, X., Hu, J.K., Song, Z.X., Huang, S.X., Zhang, J.P., 2015. The air quality of Beijinge–Tianjine–Hebei regions around the Asia-Pacific economic cooperation (APEC) meetings. Atmos. Pollut. Res. 6, 1066–1072. https://doi.org/10.1016/j.apr.2015.06.003.

Simpson, P.M., Siguaw, J.A., 2008. Perceived travel risks: the traveller perspective and manageability. Int. J. Tourism Res. 10, 315–327. https://doi.org/10.1002/jtr.664.

Song, Y., Qin, S., Qu, J., Liu, F., 2015. The forecasting research of early warning systems for atmospheric pollutants: a case in Yangtze River Delta region. Atmos. Environ. 118, 58–69. https://doi.org/10.1016/j.atmosenv.2015.06.032.

Sun, W., Zhang, H., Palazoglu, A., Singh, A., Zhang, W., Liu, S., 2013. Prediction of 24-hour-average PM2.5 concentrations using a hidden Markov model with different emission distributions in Northern California. Sci. Total Environ. 443, 93–103. https://doi.org/10.1016/j.scitotenv.2012.10.070.

Tian, C., Hao, Y., 2019. Point and interval forecasting for carbon price based on an improved analysis-forecast system. Appl. Math. Model. https://doi.org/10.1016/j.apm.2019.10.022.

Wang, J., Du, P., Hao, Y., Ma, X., Niu, T., Yang, W., 2020a. An innovative hybrid model based on outlier detection and correction algorithm and heuristic intelligent optimization algorithm for daily air quality index forecasting. J. Environ. Manag. 255, 109855. https://doi.org/10.1016/j.jenvman.2019.109855.

Wang, J., Li, H., Lu, H., 2018. Application of a novel early warning system based on fuzzy time series in urban air quality forecasting in China. Appl. Soft Comput. J. 71, 783–799. https://doi.org/10.1016/j.asoc.2018.07.030.

Wang, J., Niu, X., Liu, Z., Zhang, L., 2020b. Engineering Applications of Artificial Intelligence Analysis of the influence of international benchmark oil price on China ' s real exchange rate forecasting. Eng. Appl. Artif. Intell. 94, 103783. https://doi.org/10.1016/j.engappai.2020.103783.

Wang, J., Qin, S., Jin, S., Wu, J., 2015. Estimation methods review and analysis of offshore extreme wind speeds and wind energy resources. Renew. Sustain. Energy Rev. https://doi.org/10.1016/j.rser.2014.09.042.

Wang, J., Zhang, L., Niu, X., Liu, Z., 2020c. Effects of PM2.5 on health and economic loss: evidence from Beijing-Tianjin-Hebei region of China. J. Clean. Prod. 257, 120605. https://doi.org/10.1016/j.jclepro.2020.120605.

Wang, Z., Zhu, Y., Wang, F., Wang, P., Shen, C., Liu, J. (Eds.), 2020d. Proceedings of the 11th International Symposium on Heating, Ventilation and Air Conditioning (ISHVAC 2019), Environmental Science and Engineering. Springer Singapore, Singapore.

Xu, Y., Du, P., Wang, J., 2017. Research and application of a hybrid model based on dynamic fuzzy synthetic evaluation for establishing air quality forecasting and early warning system: a case study in China. Environ. Pollut. 223, 435–448. https://doi.org/10.1016/j.envpol.2017.01.043.

Yang, H., Zhu, Z., Li, C., Li, R., 2020. A novel combined forecasting system for air pollutants concentration based on fuzzy theory and optimization of aggregation weight. Appl. Soft Comput. J. 87, 105972. https://doi.org/10.1016/j.asoc.2019.105972.

Zhang, A., Zhong, L., Xu, Y., Wang, H., Dang, L., 2015. Tourists' perception of haze pollution and the potential impacts on travel: reshaping the features of tourism seasonality in Beijing, China. Sustain. Times 7, 2397–2414. https://doi.org/10.3390/su7032397.