ISSN 2004-2965 Energy Proceedings, Vol. 17, 2021

Paper ID APEN-MIT-2021_67
Applied Energy Symposium: MIT A+B
August 11-13, 2021 • Cambridge, USA

# Does clean coal technology policy improve air quality? Experience in China using deep learning approaches

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*Abstract*—Investigating the effect of China's clean coal technology policy on air quality is of great significance for promoting energy transformation and formulating follow-up policies. Utilizing 31 provincial cities data in Chinese mainland from 2013 to 2020, the spatial variation characteristic and change rate of air quality index (AQI) are discussed in this study. Amongst, the AQI in 2020 is predicted by deep learning approaches, to eliminate the uncertainty that COVID-19 bring about. The association analysis between AQI and socio-economic factors is also conducted, to clarify the internal mechanism of clean coal technology policy. The results show that 1) The AQI can be better predicted by the tailored Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) network; 2) the air pollution in China shows an integration trend, embodying heavy and slight pollution in Northern and Southern China, respectively; 3) the clean coal technology policy has an average reduction effect of 18.82% on AQI. And there is a 2-year time lag before the policy takes any strong positive effects; 4) the clean coal technology policy mainly improved air quality through the way of emission reduction and de-industrialization. Practicable policy suggestions are put forward to supporting emission reduction, promoting energy transformation in China and applicable to other developing countries with scarce energy resources and severe air pollution.

*Keywords—coal-based clean energy, air quality, clean coal technology policy, deep learning approaches, energy transformation*

## I. INTRODUCTION

Energy resources have played a critical role in supporting the national economic and social development. However, it has been publicly recognized that there is a contradiction between energy utilization and climate change [1][2]. As the top carbon-emitting country, many countermeasures are adopted in China, to combat the stern climate situation. A good case in point is the goal of carbon peak and carbon neutral, it is declared that China would strive to realize carbon peak by 2030 and carbon neutrality by 2060. Notably, energy production and consumption contributed significantly to the total carbon emission in China, where coal and oil-gas related emissions took up 70%-80% and 15% [3][4], respectively. Therefore, there is the objective necessity to implement energy transformation, and construct the energy system which is clean, low-carbon, safe and efficient.

However, the primary energy structure in China is coal-centered, to meet the needs of energy transformation while adapt the structure of energy industry, a circular economy industry chain in realizing clean coal utilization has been proposed, namely, "coal development--coal with high quality--clean energy--integration of coal-based materials and chemicals". In order to better fulfil the responsibility in the construction of clean coal industry, the Chinese government constantly implemented a series of laws, regulations, and policies. Two specialized action plans for promoting the clean and efficient use of coal were carried into effect in 2015, signifying that the clean and efficient use of coal in China entered the system implementation stage [5]. In addition, as 2020 is the last year of many clean coal technology policies, it is necessary to reveal the effect of the clean coal technology on air quality, with 2015 and 2020 as the prominent policy nodes.

Nevertheless, to suppress the spread of Corona Virus Disease 2019 (COVID-19), the Chinese government implemented strict lockdown, which started with Wuhan and radiated to one-third of its cities [6]. Owing to the shutdown of industrial activities and traffic volume, an obvious decline of the primary air pollutants ($NO_x$、CO、$CO_2$、$SO_2$、$PM_{2.5}$) was observed in most of cities of China during the lockdown [7][8]. Undoubtedly, this would lead to high uncertainty while investigating the effect of clean coal technology policy on air quality.

Not only clean coal technology policies, there have been heated discussions and debates over the effectiveness of China's regulatory interventions on air pollution [9]. Accordingly, a number of academic papers have emerged to work on this hot topic. However, there are some drawbacks [10][11]: On the one hand, researches are often constrained by complicated modeling processes and uncertainties in emission inventory; Besides, the relationships between air pollution and other confounding factors are overlooked in most of the publications.

Here, employing panel data of 31 provincial cities in Chinese mainland from 2013 to 2020, we assess the air quality changes pre and post policy node of clean coal technology, to obtain its effect on air quality improvement. Our study has the following three contributions: (1) The outbreak of COVID-19 would bring about uncertainties when estimating the effect of long-term policies. Our study predicts the air pollution conditions in Chinese mainland in 2020 via deep learning approaches, and results show that the tailored CNN-LSTM model has a good performance in predicting AQI. (2) Few literatures discuss the effect of clean coal technology policy on air quality improvement, with the background of coal-based clean energy transformation. Air quality data of 31 provincial cities in Chinese mainland from 2013 to 2020 is combined, to clarify whether there is positive effect of clean coal technology policy on air quality or not. (3) The evaluation process is coupled with socio-economic factors, thus the internal mechanism of clean coal technology on reducing air pollution could be investigated, which is scarce in existing publications. Our study considers the five parameters, namely, economic development, environmental governance, industrialization, population density, and social development.

## II. Data and Methods

The system architecture and main technical route of this study is depicted in Fig.1.

### A. Data collection

A total of 31 provincial cities in Chinese mainland are selected as the study area. Since the important node of clean coal technology policy is 2015, and the index describing the ambient air quality in China is reformulated after the publishment of the latest environmental air quality standard [12]. The AQI data is only available from 2013, thus the following data are extracted from 2013 to 2019 accordingly. After predicting the AQI in 2020, the investigated data covers 8 years before and after the policy node, namely, from 2013 to 2020, which is adequate for policy evaluation [13]. The collected three types of data are summarized in TABLE I. Herein, the five kinds of socio-economic data represent Economic development (ED), Environmental governance (EG), Industrialization (IL), Population density (PD), and Social development (SD), respectively.

TABLE I. Summary for three types of collected data

| ***Data Type*** | ***Introduction*** | ***Source*** |
|---|---|---|
| Air quality data | Concentrations of AQI, $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, CO, $O_3$ | https://www.aqistudy.cn/ |
| Meteorological data | Highest temperature (HT), Lowest temperature (LT), Wind direction (WD), Wind power (WP) | http://tianqi.2345.com/ |
| Socio-economic data | GDP per capita (CNY), The mean value of the removal rate of wastewater, waste gas and solid waste (%), The proportion of the secondary industry in GDP (%), The city's population per unit area (people / km$^2$), The number of civil cars (10000 vehicles) | China City Statistical Yearbook and the prefecture-level city's Statistical Bulletin of National Economic and Social Development |

### B. Data preprocessing

Considering that 2013-2015 is set as the period of before clean coal technology policy node, while 2016-2020 is after the policy node in this study, thus the air pollution condition in 2020 is predicted using the data of 2016-2019. After extraction, the daily air quality data and the daily meteorological data of 31 cities are combined to generate a tabular dataset, ranging from 22 January 2016 to 31 December 2019, which is chosen for satisfying the training of predictive network. In order to feed the subsequent neural networks with complete and low noise data, data preprocessing is conducted. The four procedures are listed as follows and shown in Fig.2. Based on the data preprocessing, a random 6:2:2 split of the data is applied as the training set, the validation set, and the test set. Correspondingly, all the input data is ready for prediction up to this point.

### C. Model training

With the rapid development of deep learning approaches, the research of air pollutant concentration prediction using such learning has become prevalent [14][15]. Herein, owing to its remarkable performance on processing time-series data, LSTM is the most frequently applied neural network in these researches [16][17]. LSTM is a variant of the Recurrent Neural Network (RNN) models, and could solve the problem of long-term dependencies that conventional RNNs cannot learn. Meanwhile, the intelligent design of memory cell in LSTM is valid for solving the problem of gradient vanishing in backpropagation, and can learn the input sequence with longer time steps.

Nevertheless, because of the diffusion effect of airborne pollutant, its change is not only related to time but also to space, while spatial information of environmental monitoring data is usually ignored using LSTM. Correspondingly, CNN is explored, whose spatial data processing capability is demonstrated to be powerful. It is proven to be valid for forecasting air pollution conditions using CNN, as the monitoring data is spatially relevant [18]. What's more, the advantage of CNN is that the training is relatively easy, and could effectively extract the important features.

Therefore, on the basis of existing researches[18][19][20][21], a predictive model combined CNN and LSTM is applied and tailored in this study, which could explain the complexity and variety of airborne pollutants, and eliminate the dependence on the historical regularity of pollutants variation. The model is built using Keras and TensorFlow. The architecture of the introduced network is shown in Fig.3. Generally, the architecture of the predictive model is an Encoder-Decoder structure. The first half of CNN-LSTM network is CNN, and utilized for feature extraction of input data. The latter half is LSTM, which is used to analyze the features extracted by CNN and then to forecast the AQI of the next point in time.

Detailedly, after the processing of the CNN part, the outputs are one-dimensional vectors with ground data features, are subsequently input to the LSTM layer. LSTM adds the time-series prediction function in this model, and its training processes are presented as equations. (1)-(6):

I. Forget phase. The LSTM first selectively forgets some input air quality data and the related parameters.

$$f_t = \sigma\,(\,W_f\,[\,h_{t-1}, x_t\,] + b_f) \tag{1}$$

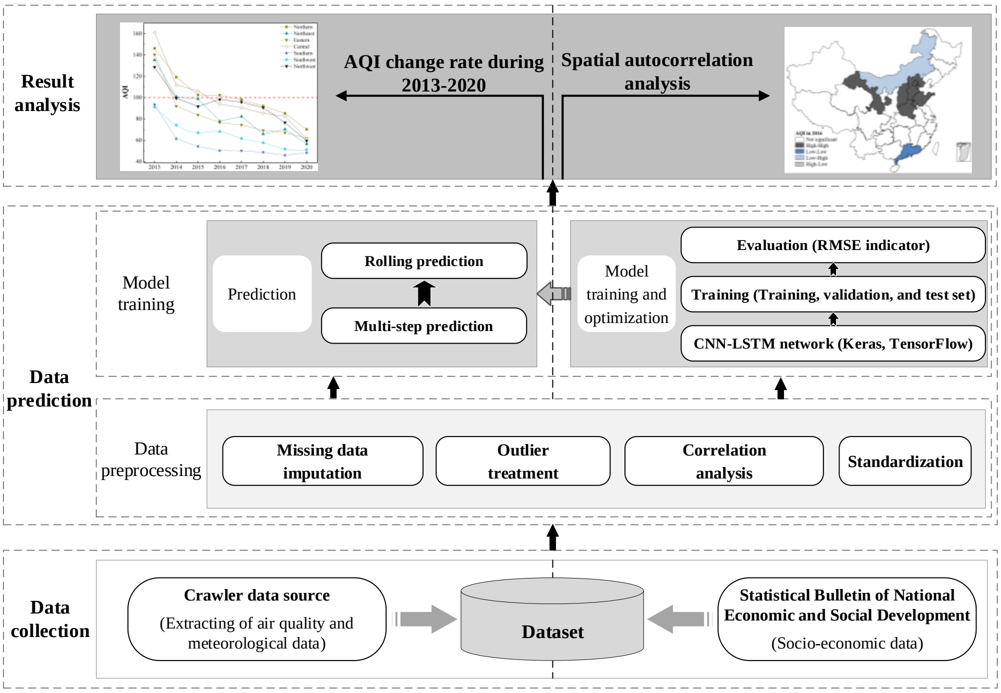


Fig. 1. The system architecture of this study based on CNN-LSTM network.

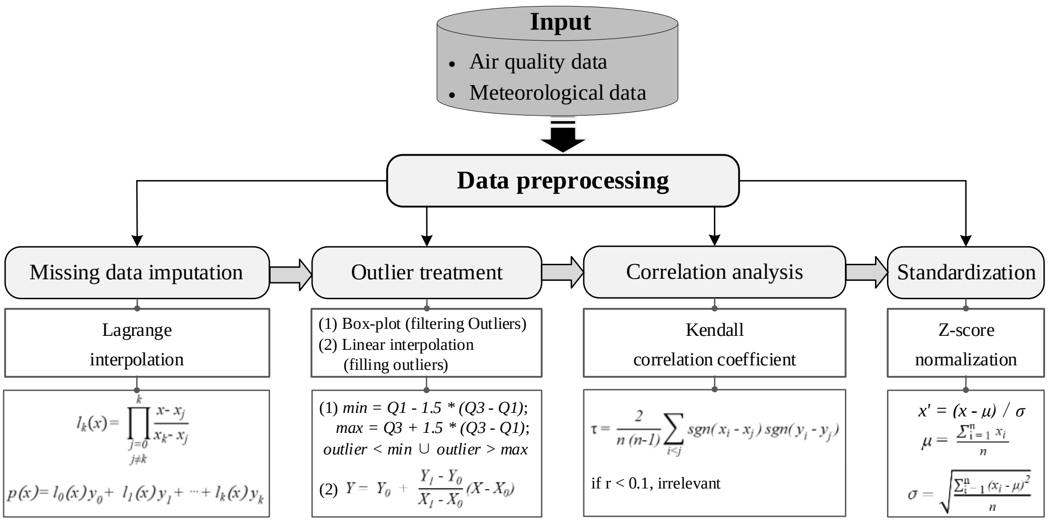


Fig. 2. Procedures, the corresponding methods and principles of data preprocessing.

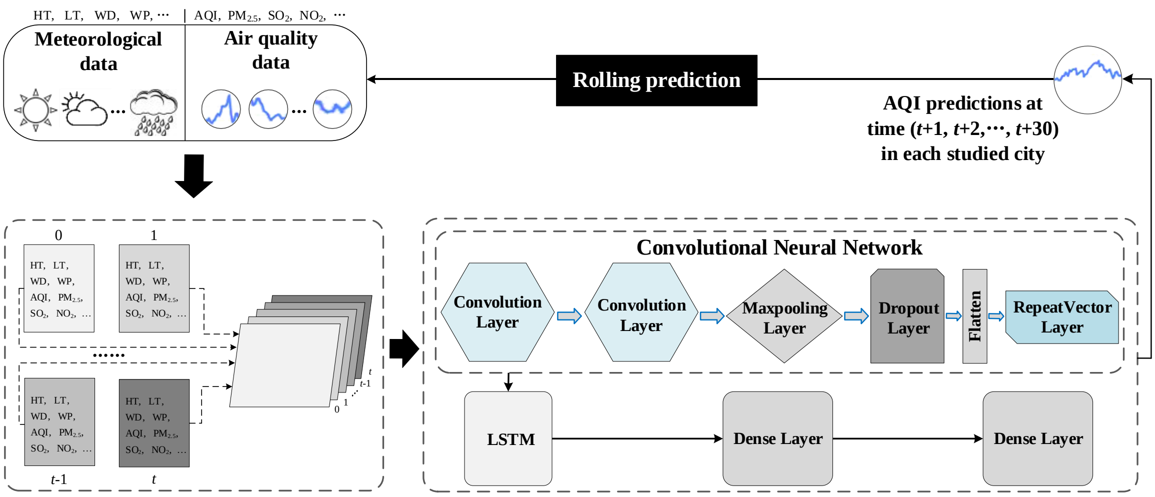


Fig. 3. The architecture of the tailored CNN-LSTM network.

II. Selective memory phase. In this phase, LSTM would decide what new information to store in the unit state, which originates from two parts. The sigmoid layer determines the updated information and the tanh layer creates a candidate value vector.

$$i_t = \sigma ( W_i [ h_{t-1}, x_t ] + b_i ) \quad (2)$$

$$C_t' = \tanh ( W_C [ h_{t-1}, x_t] + b_t ) \quad (3)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t' \quad (4)$$

III. Output phase. Deciding the outspput information, namely, the predicted AQI.

$$o_t = \sigma ( W_o [ h_{t-1}, x_t ] + b_o ) \quad (5)$$

$$h_t = o_t \odot \tanh(C_t) \quad (6)$$

where $f_t$ is the output of forget gate, $\sigma$ is the sigmoid activation function, $W_f$, $W_o$, $W_C$, $W_i$, and $b_f$, $b_o$, $b_i$, $b_t$ is the coefficient and bias of linear relationship, respectively, $h_{t-1}$ is hidden status of the last sequence, $x_t$ is the data of this sequence, it is the first part of output, $C_t'$ is the second part of output, $C_t$ is the present cell status, $C_{t-1}$ is the previous cell status, $h_t$ is the update of hidden status, $o_t$ is the update of the first hidden status, $\odot$ represents Hadamard product, requires corresponding elements in the matrix to be multiplied.

Last in the two Dense layers, the correlations among the features are extracted through nonlinear variation, and then mapped to the output space. Through rolling prediction, the sequence prediction results from output layer are added to the dataset, and continue to achieve dynamic prediction outward. Notably, in order to improve the performance and effect of learning, the hyper-parameters are adjusted and optimized before learning for different studied city, namely, for different input datasets. To assess the error of prediction processing, Root Mean Square Error (RMSE) is applied. RMSE quantifies the dispersion between predicted and actual data, and the smaller the value is, the better the performance of predictive model. The measurement indexes with its equation are shown in equation (7).

$$\mathrm{RMSE} = (1/N \sum_{i=1}^{N} (P_i - O_i)^2)^{1/2} \quad (7)$$

where $N$ is the number of test samples, $P_i$ is the predicted air pollutant concentration, $O_i$ is the observed air pollutant concentrations.

## D. Spatial autocorrelation analysis

To further analyze the temporal and spatial variation features of air quality of 31 central cities in Chinese mainland, spatial autocorrelation analysis method is applied, ranging from 2013 to 2020. ArcGIS 10.6 and GeoDa software are used to realize the calculation and analytic process.

### a) Global spatial autocorrelation analysis

First, the global spatial autocorrelation analysis method is utilized to reflect the space gathering of AQI. The calculation formulas of global Moran's I are listed as Equations. (8)-(9), and its significant testing is conducted by Equation. (10).

$$\mathrm{I} = \sum_{i=1}^{n} \sum_{j=1}^{n} ( w_{ij} (x_i - \bar{x})(x_j - \bar{x}) / S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \quad (8)$$

$$S^2 = 1/n \sum_{i=1}^{n} (x_i - \bar{x})^2 \quad (9)$$

$$Z(I) = I-E(I) / (Var(I))^{1/2} \quad (10)$$

where $S^2$ is the variance of attribute value, n represents 31 studied cities, $x_i$, $x_j$ is the AQI value of city i, j, respectively, $\bar{x}$ is the average AQI of all cities, $w_{ij}$ is spatial weight, $E(I)$ is the mean of global Moran's I, $Var(I)$ is the variance of global Moran's I, $Z(I)$ is the significance level of global Moran's I. The range of global Moran's I is -1 to 1, if it is greater than 0, indicating the spatial distribution of AQI is positive; if less than 0, indicating a negative correlation; if equals to 0, indicating a random distribution.

### b) Regional spatial autocorrelation analysis

Second, the highly and slightly polluted areas before and after policy node in these 31 cities are clarified through regional spatial autocorrelation analysis method, the calculation process of regional Moran's I is shown as Equation. (11).

$$I_i = (x_i - \bar{x}) / S^2 \sum_{j=1} w_{ij}(x_j - \bar{x}) \quad (11)$$

The significant level of regional Moran's I is tested by Equation. (10) as well. If regional Moran's I is greater than 0 and is significant, suggesting there is high-high or low-low gathering area; if it is less than 0 and is significant, suggesting high-low or low-high gathering areas.

## E. Measuring AQI change rate during 2013 – 2020

To make a fuller understanding regarding the improved air quality, a comparison is made between AQI pre and post the set policy node. To do so, 2013-2015 is taken as pre node year, and change of AQI is computed for 2016-2020 as after policy node. Equation. (12) is the mathematical formulation of the AQI's change rate calculation.

$$C_{AQI} = (pr_{AQI} - po_{AQI}) / pr_{AQI} \times 100\% \quad (12)$$

where $C_{AQI}$ is the change rate of AQI for each studied city, $pr_{AQI}$ is the average AQI of each month for studied cites from 2013 to 2015, $po_{AQI}$ is the average AQI of each month for studied cites from 2016 to 2020. The calculated results vary between -100% to 100%, where negative and positive values indicate improvement or deterioration of air quality, and 0 represents no change.

## F. Investigating the association between AQI and confounding factors

To discuss the relationship between air quality change and socio-economic factors, and further explore the internal mechanism of clean coal technology policy working on air quality improvement, correlation analysis is conducted with the help of SPSS 28.0 software. More specifically, the correlation degree is calculated with all socio-economic variables separately for each year. Based on this, we assume there is a linear correlation between $C_{AQI}$, and ED, EG, IL, PD, and SD, the proposed analysis model is shown as Equation. (13). Ordinary Least Square (OLS) regression is also carried out, and the variance inflation factor of each variable is computed to verify the existence of multicollinearity of this model.

$$\ln C_{AQI} = a_0 + a_1 \ln \Delta ED + a_2 \ln \Delta EG + a_3 \ln \Delta IL + a_4 \ln \Delta PD + a_5 \ln \Delta SD \quad (13)$$

where $\Delta ED$, $\Delta EG$, $\Delta IL$, $\Delta PD$, and $\Delta SD$ are the change of ED, EG, IL, PD, and SD pre and post clean coal technology policy node, $a_0$, $a_1$, …, $a_5$ are the model parameters.

## III. RESULTS ANALYSIS

### A. Performance of the CNN-LSTM model

As mentioned above, the extracted data including a total of 1440-day air quality and meteorological data (January 22, 2016 to December 31, 2019) of 31 provincial cities in Chinese mainland, 60% of which are chosen as the training set, 20% as the validation set and 20% as the test set. After determining the best basic network architecture for the current prediction tasks, models are set up in units of cities, and the training set is used to train the tailored CNN-LSTM models. The RMSE value is obtained to evaluate model performance, with the average of 22.06.

### B. Spatial change characteristics of air quality

#### a) Results of global spatial autocorrelation analysis

The global spatial autocorrelation analysis is carried out using the average of monthly AQI for 31 studied cities from 2013 to 2020. The results of global Moran's I are all greater than 0, and are significant under significance testing. Correspondingly, that could signify there are significant and positive spatial correlations among the average of monthly AQI.

#### b) Spatial pattern representing in north - south differentiation

Through global spatial autocorrelation analysis, the space gathering of air pollution is proven to exist. Furthermore, to definitely point out the gathering district, the results of regional spatial autocorrelation is also obtained. As shown in Fig.4, it could be found that there still are high-high gathering areas (Heavy pollution) and low-low gathering areas (Slight pollution) from 2013 to 3030. Meanwhile, a north - south spatial heterogeneity pattern is obvious, embodying heavy pollution in Northern China, and slight pollution in Southern China.

From the perspectives of heavy pollution zones' variation characteristics, an unicentric pattern centered by Northern China could be found easily from 2013 to 2015, namely, before the clean coal technology policy node. Ranging from 2016 to 2020, although the air quality was improved in general, relatively speaking, the high polluted zones enlarged. Detailedly, expanding to Northwest and Northeast China. Regarding the variation characteristics of slight pollution zone, there are two spatial patterns in general, namely, the monocentric pattern centered by Southern China, bicentric pattern centered by Southern China and south of Southwest China. Specifically, from 2013 to 2015, the slight polluted area in the nationwide mainly locates in Southern China. After the clean coal technology policy node, the regional distribution of slight polluted area scattered to the south of Southwest China gradually. Amongst, it could be observed in 2019 most easily.

### C. Effect of clean coal technology policy on air quality

If the comparison is done at a temporal scale, it is evident that the AQI in Chinese mainland had considerably reduced from 2013 to 2020. As shown in Fig.5, AQI of all studied cites are all less than 100 from 2017, which is the threshold AQI value of excessive pollutants, and is decreasing year by year. Herein, for better classification and comparison, the 31 provincial cities are categorized into 7 districts according to the official administrative geographical areas dividing. Correspondingly, quite an identical trend is seen in the case of Central China, whose air quality improvement is the greatest covering the time span from 2013 to 2020.

For better understandability of policy effect on AQI, the change rate is computed between pre and post policy node. TABLE II lists the percentage change of AQI in 31 cities of Chinese mainland. Out of the total area, 100% area experienced improvement of air quality, with the change rate of AQI ranging from 29.54% to 4.28%. Regionally, the degree of improvement was maximum in Central China (25.61%), followed by Northeast (25.47%), Eastern (20.88%), and Northern China (18.30%). And the three districts which have the least improvement are Northwest, Southern, and Southwest China, with the change rate of 15.27%, 14.63%, and 14.44%, respectively. On average, the AQI value are reduced by 18.82% in Chinese mainland from 2013 to 2020, indicating that with the implementation of clean coal technology policy, China's air quality is improved to a great extent.

### D. Mechanism analysis of clean coal technology policy on air quality

To further analyze the specific mechanism of the clean coal technology policy to improve air quality, a correlation analysis between air quality change and socio-economic factors is conducted. Herein, if the coefficient is greater than 0, indicating there is a positive relationship between the decrease of AQI and socio-economic factors; if less than 0, indicating a negative relationship. Besides, the variance inflation factors of each variable are computed through OLS method, ranging from 1.007 to 2.297, all less than the threshold of 10, indicating that there is no multiple collinearity issue in this linear correlation model [22].

As depicted in Fig.6, we find that there is no significant correlation (coefficients greater than 0.6) between the change of AQI and socio-economic factors. However, an obvious phenomenon is that the increase of the environmental governance, and the decrease of industrialization are positively related to the air quality improvement. Further, the increase of economic development, population density, and social development are all negatively related to the air quality improvement. Relating to the coal-based clean energy industry, we can conduct that the clean coal technology policy mainly reduced air pollution through countermeasures on emission reduction and de-industrialization.

## IV. POLICY IMPLICATIONS

In this study, we estimate the changes in AQI from 2013 to 2020, to show the effect of clean coal technology policy on air quality. To the best of our knowledge, this is the first study comprehensively assessing the air quality improvement against the background of coal industry's energy transformation at the national level. According to the research findings, we believe that it could offer practical references from four dimensions:

### A. Support environmental monitoring

Through our work, we could conclude that pre and post policy node, Northern China is always at a higher pollution level compared to other districts, while Southern and Southwest China are two main districts whose air pollution

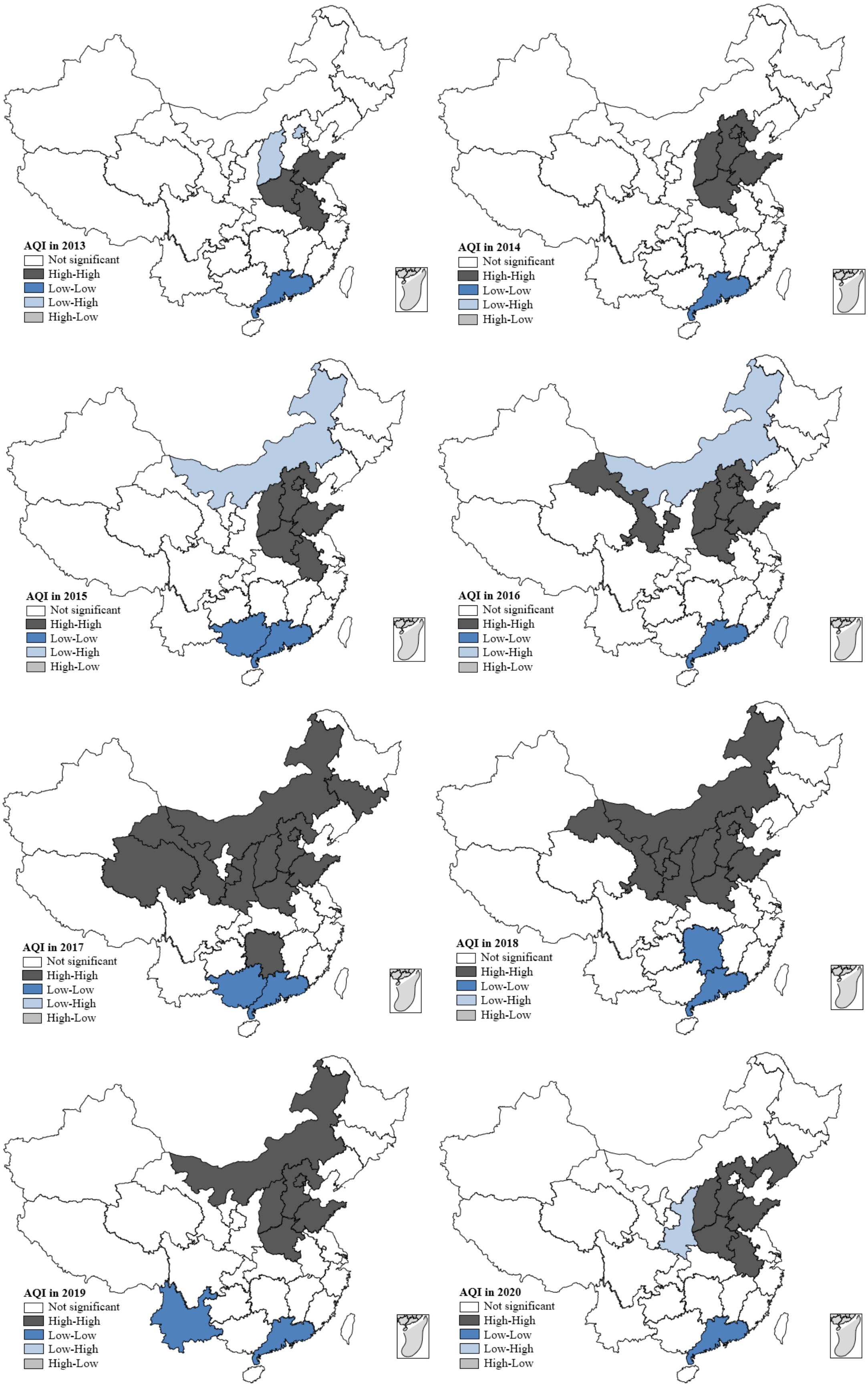


Fig. 4. The analysis of AQI regional spatial autocorrelation in 31 provincial cities of Chinese mainland.

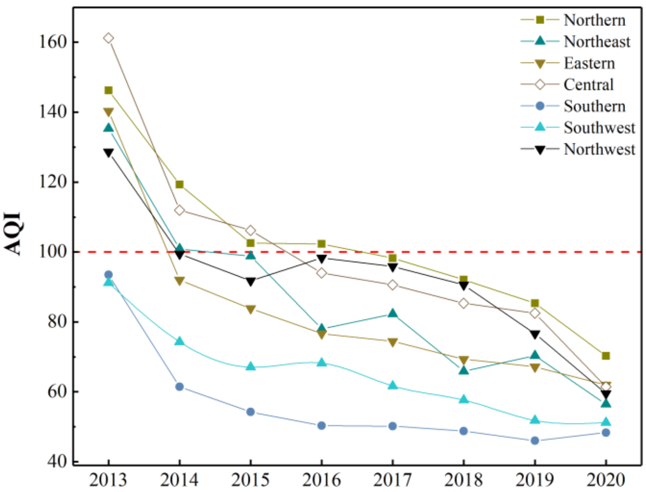


Fig. 5. The variation trend of AQI in Chinese mainland.

TABLE II. THE CHANGE RATE OF AQI PRE AND POST CLEAN COAL TECHNOLOGY POLICY NODE (UNIT: %)

| ***District*** | ***City*** | $C_{AQI}$ | ***District*** | ***City*** | $C_{AQI}$ |
|---|---|---|---|---|---|
| Northern | Beijing | 26.46 | Southwest | Chongqing | 18.58 |
| | Tianjin | 22.47 | | Chengdu | 19.16 |
| | Shijiazhuang | 27.60 | | Guiyang | 20.83 |
| | Taiyuan | 4.28 | | Kunming | 6.30 |
| | Huhhot | 10.70 | | Lasa | 7.34 |
| Northeast | Shenyang | 25.26 | Southern | Guangzhou | 15.52 |
| | Changchun | 26.40 | | Nanning | 21.66 |
| | Harbin | 24.75 | | Haikou | 6.72 |
| Northwest | Xi'an | 11.69 | Eastern | Shanghai | 21.01 |
| | Lanzhou | 10.10 | | Nanjing | 27.48 |
| | Xining | 17.62 | | Hangzhou | 21.93 |
| | Yinchuan | 17.62 | | Hefei | 24.09 |
| | Urumqi | 19.34 | | Fuzhou | 14.28 |
| Central | Zhengzhou | 22.47 | | Nanchang | 10.92 |
| | Wuhan | 29.54 | | Jinan | 26.42 |
| | Changsha | 24.82 | | | |

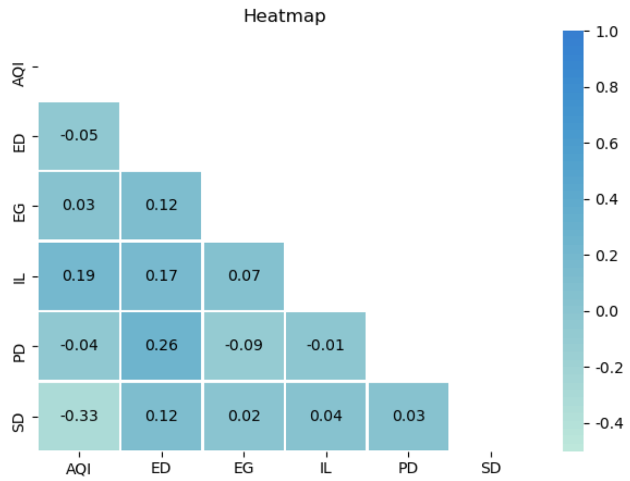


Fig. 6. Correlation coefficients between air quality change and socio-economic factors.

levels are slighter. Accordingly, the related department would have an overview of cities, provinces, and districts that need to be supervised in priority, the insights into allocating the environmental regulatory resources are provided as well.

### *B. Enhance consensus building*

Actually, the public are not adequately aware of the efficiency of clean coal technology policy. More often, the whole society would consider the implementation of clean air policy as useless, misled by the occurrence of extreme inclement weather. Nevertheless, the positive effect of clean coal technology policy on air quality improvement is verified, showing an average reduction of 18.82%. Therefore, this study will help to guide society in shaping scientific cognition above the influence of clean coal technology on improving air quality. Moreover, references could be presented for energy companies, coal companies and related industry organizations to correctly grasp the direction of power development.

### *C. Promote policy making*

It is a transformation period of Chinese energy structure from 2020 to 2030, the formulation of industrial policy in this period should provide a basis for long-term energy transformation. And the 14$^{th}$ Five-Year period (2021-2025) is also critical for China's energy transition and climate change response. Through assessing the effect of clean coal technology policy on atmospheric emission reduction, it is expected to timely provide a reference for the government to establish subsequent laws, policies, and regulations.

### *D. Facilitate international coordination*

By verifying the effect of clean coal technology policy on air quality in China, practical policy experiences can be used for reference by other developing countries with scarce energy resources and severe air pollution. Meanwhile, it would be beneficial to reasonably share responsibilities for the international goal of tackling climate change among countries, also preventing the transboundary effects of air pollution.

## V. CONCLUSIONS

Using the panel data of 31 provincial cities in Chinese mainland from 2013 to 2019, the AQI in 2020 is predicted with the help of deep learning approaches, to eliminate the influence of COVID-19 on the actual condition of air pollution. Moreover, after obtaining the complete AQI dataset from 2013 to 2020, the effect of clean coal technology policy on air quality is investigated. Herein, to grasp the spatial variation characteristics of AQI before and after the policy node, and further clarify the internal mechanism of clean coal technology policy on air quality improvement, the spatial autocorrelation analysis and association test between AQI and socio-economic factors are conducted. The main conclusions are as follows.

First, the AQI can be predicted in a good performance using the CNN-LSTM network tailored in this study, which could embody the complex relationship between AQI and other confounding factors, i.e., concentrations of $PM_{2.5}$, $PM_{10}$, $SO_2$, $CO$, $NO_2$, and $O_3$, and meteorological data of temperature, wind direction, and wind power.

Second, the integration trend of air pollution in China is evident, embodying heavy pollution in Northern China, and slight pollution in Southern China for the most time. More importantly, our findings propose that the clean coal technology policy has significantly improved overall air quality in Chinese mainland, with the average reduction of 18.82%. Amongst, covering the time span from 2013 to 2020, the AQI of central China decreased the most.

Lastly, the effect of clean coal technology policy on air quality improvement is significantly observed from 2018, indicating a 2-year time lag before the policy takes strong positive influences. Finally, the mechanism analysis shows that clean coal technology policy not only directly reduces air pollution through promoting emission reduction, but also indirectly decrease air pollution via de-industrialization.

## ACKNOWLEDGMENT

The study was financially supported by the National Natural Science Foundation of China (No. 52074302), and the Natural Science Foundation of Beijing Municipality (No. 8212015).

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