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Spatiotemporal Analysis and Deep Learning-Based Prediction of Air Pollution in China, 2015–2024

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Abstract

Air quality in China has markedly improved over the past decade, yet pollution levels remain high and continue to threaten public health. This study analyzed the spatiotemporal variations in six air pollutants (PM_{2.5}, PM₁₀, SO₂, NO₂, O₃, CO) across seven regions in China (2015–2024) using Kriging interpolation. The performance of Recurrent Neural Network (RNN), Long Short-term Memory (LSTM), and Convolutional Neural Network-Long Short-term Memory (CNN-LSTM) models was assessed using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R²) metrics. Results showed that all pollutants exhibited overall declining trends, with SO₂ depicting the largest reduction (69.53%), while O₃ displayed intermittent increases from 2017 to 2024. North China recorded both the highest concentrations and the greatest reductions in PM_{2.5}, SO₂, and CO, whereas Southwest and South China maintained the lowest overall levels. Among the predictive models, LSTM achieved the highest overall accuracy (mean RMSE = 1.802, mean MAE = 0.915, R² > 0.99). These findings provide a comprehensive depiction of China's air pollution evolution and highlight the potential of deep learning for region-specific air quality prediction and policy design. The results offer a quantitative foundation for optimizing differentiated control strategies and advancing precision air quality management.

Keywords: criteria air pollutants; spatiotemporal patterns; time series forecasting; deep learning; regional variability

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1. Introduction

With rapid economic growth and industrialization, air pollution has emerged as a major global environmental challenge. Exposure to air pollutants is closely linked to respiratory and cardiovascular diseases, substantially increasing morbidity and mortality [1]. Air pollution contributes to roughly one-quarter of the global disease burden, causing

about seven million deaths annually [2]. The primary indicators used to assess air quality include fine particulate matter ($PM_{2.5}$), inhalable particulate matter (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO)—collectively known as criteria pollutants. According to the World Health Organization (WHO), nearly 90% of the global population breathe air that exceeds WHO guideline limits [3]. As a representative developing country, China experiences pollution levels far above WHO recommendations. However, systematic research into the spatiotemporal evolution of the six criteria pollutants—particularly at national and regional scales—remains limited. Therefore, accurately assessing current air quality, analyzing the spatial and temporal distribution of pollutants, and revealing their regional variations and long-term trends are essential for effective air quality management.

In early 2013, a severe and persistent haze event affected extensive regions of eastern and central China, impacting nearly 800 million people [4]. This episode marked a turning point in China's air quality management, prompting rapid implementation of nationwide pollution control initiatives. To curb further environmental deterioration and mitigate health risks, the Chinese government introduced a series of comprehensive policies, including the Air Pollution Prevention and Control Action Plan (2013–2017), Three-Year Action Plan (2018–2020), and Air Quality Sustained Improvement Action Plan (2023–2025) [5]. By 2024, the national average $PM_{2.5}$ concentration in prefecture-level cities and above had decreased by 2.7%, while the proportion of days with good air quality increased to 87.2%. These results underscore the substantial progress achieved through recent pollution control and ecological protection efforts. However, the long-term air pollution outlook remains challenging, and its associated health risks continue to demand sustained attention and intervention.

Accurate and reliable prediction of air pollutant concentrations is vital for public health protection and atmospheric environmental management. Current air quality forecasting models can be broadly categorized into two major types: physical models and empirical models [6].

Physical models—such as the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem) [7] and the Community Multiscale Air Quality model (CMAQ) [8]—use mathematical formulations to simulate atmospheric processes, including pollutant dispersion, deposition and chemical interactions [9]. However, the nonlinear nature of atmospheric systems introduces parameter uncertainties that can lead to prediction biases. Furthermore, their complex and highly constrained structures limit scalability and applicability over large spatial domains [10].

In contrast, empirical models rely on historical data from monitoring stations and use statistical or machine learning techniques to establish predictive relationships [11]. Traditional statistical models, including Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) [12], perform poorly with nonlinear and high-dimensional data. More recently, machine learning methods—such as Support Vector Machine (SVM) [13], Multilayer Perceptron (MLP) [14], and Random Forest (RF) [15]—have been applied to air quality prediction [16]. These approaches learn input-output mappings effectively but remain limited by the shallow architecture's inability to capture complex spatiotemporal dependencies.

In recent years, deep learning techniques have been increasingly applied to global air pollution prediction due to their strong capability to capture spatiotemporal features, often outperforming traditional machine learning models [17]. Among these methods, Recurrent Neural Networks (RNNs) demonstrate superior performance in time-series forecasting compared to linear regression and other non-recurrent architectures [18]. Long Short-Term Memory (LSTM) networks, an advanced variant of RNNs, effectively address the vanishing gradient problem through the use of memory cells [19], enabling them to

capture long-term dependencies critical for accurate concentration prediction. Consequently, LSTM models have seen widespread adoption in air quality research [20].

Another effective approach for modeling spatiotemporal data integrates Convolutional Neural Networks (CNNs) with LSTM layers in a hybrid CNN-LSTM architecture [16]. This model combines CNN's strength in spatial feature extraction with LSTM's capacity for temporal sequence modeling, making it a prominent focus in recent studies. Overall, these deep learning frameworks provide powerful tools for processing large-scale, nonlinear air pollution time-series data and achieving high-precision predictions.

This study employed a comprehensive 10-year dataset (2015–2024) of six monitored air pollutants across China. The objectives were to: (1) map long-term spatiotemporal patterns of pollutant concentrations; (2) develop and compare three deep learning models—RNN, LSTM, and CNN-LSTM; and (3) evaluate policy effectiveness and propose future mitigation strategies. The findings of this study provide scientific support for environmental authorities in formulating targeted pollution control policies and offer valuable references for public health agencies to develop adaptive population health protection strategies.

2. Data and Methods

2.1. Study Region

This study focused on the seven geographical regions of mainland China, defined according to the national administrative participation system [21]: Northeast China, North China, Central China, South China, East China, Northwest China, and Southwest China. The regional divisions are shown in detail in Figure 1.



Figure 1. Geographic division of mainland China into seven regions.

2.2. Data Sources

Hourly concentration data for PM_{2.5}, PM₁₀, SO₂, NO₂, O₃, and CO were obtained from the China National Environmental Monitoring Centre (CNEMC) platform [22,23], covering the period from 1 January 2015 to 31 December 2024. For analysis, PM_{2.5}, PM₁₀, SO₂,

NO₂ and CO concentrations were expressed as 24 h means, while the O₃ concentrations were presented by the daily maximum 8 h mean.

2.3. Visualizing Spatiotemporal Distribution Characteristics

To ensure the data validity of air pollutant concentrations, strict quality control procedures were applied. Data preprocessing was performed in R (Version 4.5.0) to identify and remove outliers and anomalies. First, zero and missing hourly concentrations values were excluded. Second, when calculating daily means, data were considered invalid and removed if more than 4 h of a given day were missing or invalid. Third, monthly means were calculated, only when each month contained at least 27 valid days (≥ 25 days for February). Finally, annual means were calculated only if the valid data were available for at least 324 days within in the year [24].

The Z-score method was applied to standardize the hourly time series of air pollutant concentrations. Outliers were identified according to the following criteria: (1) an absolute Z-score greater than 4 ($|z_t| > 4$); (2) an increase from the previous value exceeding 9 ($z_t - z_{t-1} > 9$); (3) a ratio of the current value to its centered 3-point rolling mean (RM₃) greater than 2 ($z_t/\text{RM}_3(z_t) > 2$) [25].

ArcGIS Pro (Version 3.4) was used to visualize the spatiotemporal distribution of air pollutants through the Kriging spatial interpolation method, which reveals regional variations and long-term trends. This geostatistical approach, based on regionalized variables and variograms, applies linear, unbiased, and optimized estimation to accurately represent the data's spatial continuity and variability [26]. The Kriging interpolation formula is expressed as

$$Z_0 = \sum_{i=1}^n \lambda_i Z_i$$

where Z_0 is the estimated value at location (x_0, y_0) , n is the number of sample points used for interpolation, λ_i is the weight coefficient, and Z_i is the observed value at location (x_i, y_i) .

Kriging was selected as the primary method for three reasons. First, the CNEMC observations constitute a single national monitoring network, and the data were tested and found to generally satisfy the stationarity assumption required by Kriging. Second, the study aims to reveal the spatial patterns of air pollutants over a long period and large spatial extent, rather than focusing on detailed modeling of local outliers or small-scale variations, for which Kriging is sufficiently robust. Third, given the computational burden of batch interpolation involving ten years, multiple regions and six pollutants, Kriging offers higher computational efficiency. Accordingly, annual mean concentrations were interpolated using Kriging under a unified projection. Experimental variograms were fitted using Gaussian models, with parameters selected by minimizing cross-validation errors. Model performance was evaluated using cross-validation at monitoring sites ($n = 336$).

2.4. Constructing the Prediction Model

2.4.1. Data Preprocessing and Model Parameter Settings

Data preprocessing was performed using Python (Version 3.7.16) prior to model development. Missing values were identified and removed, and Min-Max normalization was applied to scale pollutant concentrations, facilitating model convergence and reducing redundant data [27]. For the all models, 80% of the data were used for training and 20% for testing.

Neural network performance depends heavily on model parameter settings [21]. Mean Squared Error (MSE) was employed as the loss function, and the Adam optimizer was applied with a learning rate of 10^{-3} for 100 iterations. The RNN, LSTM, and CNN-

LSTM models contained 7525, 5985, and 99,846 trainable parameters, respectively. Additional model parameters are provided in Table 1.

Table 1. Parameter configurations of the RNN, LSTM, and CNN-LSTM models.

	Layer (Type)	Output Shape	Parameter #
RNN	simple_rnn (SimpleRNN)	(None, 64)	4224
	dense (Dense)	(None, 50)	3250
	dense_1 (Dense)	(None, 1)	51
LSTM	lstm (LSTM)	(None, 32)	4352
	dense (Dense)	(None, 48)	1584
	dense_1 (Dense)	(None, 1)	49
CNN-LSTM	input_1 (Inputlayer)	(None, 10, 1)	0
	conv1d (Conv1D)	(None, 8, 64)	256
	max_pooling1d (MaxPooling1D)	(None, 4, 64)	0
	reshape (Reshape)	(None, 4, 64)	0
	lstm (LSTM)	(None, 128)	98,816
	dense (Dense)	(None, 6)	774

Note: # denotes the number of trainable parameters in each layer.

2.4.2. RNN

Recurrent Neural Networks (RNNs) are a fundamental class of neural network for processing sequential data [28]. Their core mechanism is the recursive propagation of hidden states, enabling the network to dynamically integrate information from previous time steps when processing the current input. Specifically, RNNs feature recurrent connections along the temporal dimension: neurons receive both the current input and the hidden state output from the previous time step. This unique recurrent feedback endows RNNs with memory capabilities, enabling outputs to depend on both current inputs and the accumulated information from all relevant past inputs. The RNN architecture can be expressed mathematically as

$$S_t = f(UX_t + WS_{t-1} + b_s)$$

$$O_t = g(VS_t + b_o)$$

where X_t is the input at time t , S_t is the hidden state at time t , and O_t is the output at time t . U and V are weight matrices from the input to hidden layer and hidden to output layer, respectively. W is the weight matrix connecting the previous hidden state to the current hidden state, and b_s and b_o are bias parameters.

2.4.3. LSTM

Long Short-Term Memory (LSTM) networks, a widely used deep learning model, effectively addresses the vanishing and exploding gradient problems encountered by RNNs during long-sequence training. This is achieved through a unique gating mechanism that iteratively updates the network's memory, enabling LSTM to capture long-term dependencies.

The LSTM architecture comprises four key components: the input gate, forget gate, memory cell, and output gate, which collectively regulate the retention and discarding of information from previous and current states. The input gate controls how new information influences the memory cell, the forget gate determines which information to discard, the memory cell stores and transmits information, and the output gate governs the information passed to the next time step [27]. Mathematically, the LSTM is expressed as:

The inputs to each gate of a LSTM unit consist of the current time step input X_t and the hidden state of the previous time step H_{t-1} , which are calculated by a fully connected layer with the sigmoid activation function. The values of all three gating units is $[0, 1]$. The input gate I_t , the forget gate F_t , and the output gate O_t are computed as follows:

$$F(t) = \sigma(W_f[H_{t-1}, X_t] + b_f)$$

$$I(t) = \sigma(W_i[H_{t-1}, X_t] + b_i)$$

$$O_t = \sigma(W_o[H_{t-1}, X_t] + b_o)$$

where F , I , and O are the forget, input and output gate, respectively. X is the input, H is output, and C is the cell state. W_f , W_i and W_o are input weight matrices, while b_f , b_i and b_o are bias terms. σ denotes the sigmoid activation function.

The candidate memory cell $\tilde{C}_t$ is computed in a manner similar to the input gate, output gate, and forget gate, but with a different activation function. Specifically, Tanh is used as the activation function, whose range is $(-1, 1)$. The calculation formula at time step t is

$$\tilde{C}_t = \tanh(W_c[H_{t-1}, X_t] + b_c)$$

where W_c and U_c are input weight matrices, while b_c is bias terms.

In LSTM, there is a mechanism to control input and forgetting: the input gate I_t determines how much new information from the candidate memory cell C_t is adopted, while the forget gate F_t controls how much of the past memory cell C_{t-1} is retained. The memory cell at time step t is obtained through element-wise multiplication:

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t$$

where $\odot$ denotes element-wise multiplication.

If the forget gate is always 1 and the input gate is always 0, the past memory cell C_{t-1} will be preserved over time and passed to the current time step. Finally, the hidden state H_t needs to be calculated, which is where the output gate comes into play. The calculation is as follows:

$$H_t = O_t \odot \tanh(C_t)$$

When the output gate is close to 1, it can effectively transfer all the memory information to the prediction component. When the output gate is close to 0, all the information within the memory cell is retained without the need to update the hidden state.

2.4.4. CNN-LSTM

The CNN-LSTM hybrid model effectively combines CNN's spatial feature extraction capabilities with LSTM's strength in capturing temporal dependencies, enabling efficient prediction of complex air pollutant dynamics. This architecture is particularly effective in distinguishing between stationary and non-stationary data [29]. During training, the CNN component uses convolutional layers to extract latent features from pollutant concentration data, while pooling layers reduce feature dimensionality and highlight key patterns, facilitating faster training. Subsequently, the processed features are passed to the LSTM layers to capture long-term temporal dependencies, followed by a fully connected layer for prediction, with parameters optimized to maximize model accuracy. Detailed methods can be found in the Supplementary Materials.

2.4.5. Model Evaluation Indicators

The predictive accuracy of the three models was evaluated using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2)

to identify the optimal model. The RMSE quantifies the deviation between predicted and observed values, reflecting overall prediction accuracy; MAE provides an intuitive measure of model error, with lower values indicating higher precision; and R^2 assesses the goodness of fit between predicted and observed values, with values closer to one denoting superior performance. In general, better predictive performance is indicated by higher R^2 values combined with lower MAE and RMSE values [16]. The metrics are calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$R^2 = \frac{\sum_{i=1}^n (y_i - \hat{y}_i \bar{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2}$$

where n is the sample size, y_i is the observed value of the air pollutant concentration, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the observed values.

3. Results

3.1. Spatiotemporal Trends and Regional Variations in Air Pollution, 2015–2024

From 2015 to 2024, air quality in China markedly improved (Figures 2 and S1–S4). The annual mean pollutant concentrations are summarized in Table S1 and show that overall, the concentrations of all six major air pollutants declined. SO_2 exhibited the largest reduction (69.53%), followed by CO (40.98%), $\text{PM}_{2.5}$ (38.31%), PM_{10} (36.76%), and NO_2 (30.89%), while O_3 showed the smallest decrease (15.80%). Concentrations of SO_2 and CO continued to steadily decline, whereas $\text{PM}_{2.5}$, PM_{10} , and NO_2 displayed synchronized fluctuations, increasing during 2016–2017 and 2022–2023. O_3 concentrations increased during 2017–2018 and 2021–2024, though the rate of increase slowed after 2023. According to the updated WHO Air Quality Guidelines (September 2021) [30], China's 2024 national annual mean concentrations of $\text{PM}_{2.5}$ ($30.53 \mu\text{g}/\text{m}^3$) and PM_{10} ($54.43 \mu\text{g}/\text{m}^3$) met Interim Target I thresholds ($<35 \mu\text{g}/\text{m}^3$ for $\text{PM}_{2.5}$ and $<70 \mu\text{g}/\text{m}^3$ for PM_{10}) and NO_2 ($20.65 \mu\text{g}/\text{m}^3$) met the Interim Target II threshold ($<30 \mu\text{g}/\text{m}^3$ for NO_2).

Over the past decade, Southwest and South China consistently exhibited the lowest annual mean concentrations of all air pollutants among the seven geographical regions. In contrast, North China recorded the highest annual mean concentrations of $\text{PM}_{2.5}$ ($49.13 \mu\text{g}/\text{m}^3$), PM_{10} ($93.64 \mu\text{g}/\text{m}^3$), SO_2 ($21.87 \mu\text{g}/\text{m}^3$), NO_2 ($35.53 \mu\text{g}/\text{m}^3$) and CO ($1 \text{ mg}/\text{m}^3$), while the peak O_3 concentration ($75.95 \mu\text{g}/\text{m}^3$) occurred in East China. SO_2 showed the most substantial decline across all regions, with reductions exceeding 50% nationwide. The largest decreases in annual mean concentrations were observed for $\text{PM}_{2.5}$ (44.9%), SO_2 (83.34%), and CO (58.4%) in South China; PM_{10} (40.95%) and NO_2 (39.4%) in Central China; and O_3 (21.34%) in South China. Conversely, Northwest China experienced the smallest reductions in $\text{PM}_{2.5}$ (29.87%), PM_{10} (26.35%), and NO_2 (22.51%). Significant downward trends in $\text{PM}_{2.5}$ and PM_{10} were evident in all regions except Northwest China (Table 2).

Table 2. Percentage reduction in air pollutant concentrations across China's regions from 2015 to 2024.

Region	CO	NO_2	O_3	$\text{PM}_{2.5}$	PM_{10}	SO_2
North China	58.40%	34.60%	10.97%	44.90%	38.90%	83.34%

Northeast China	35.79%	27.19%	19.72%	38.79%	37.91%	69.96%
East China	38.13%	33.11%	14.86%	42.52%	40.31%	71.76%
Central China	46.33%	39.40%	10.51%	39.11%	40.95%	73.64%
South China	34.59%	28.65%	21.34%	37.16%	33.18%	50.30%
Southwest China	31.46%	29.29%	15.99%	33.64%	39.59%	59.15%
Northwest China	44.62%	22.51%	16.31%	29.87%	26.35%	66.30%

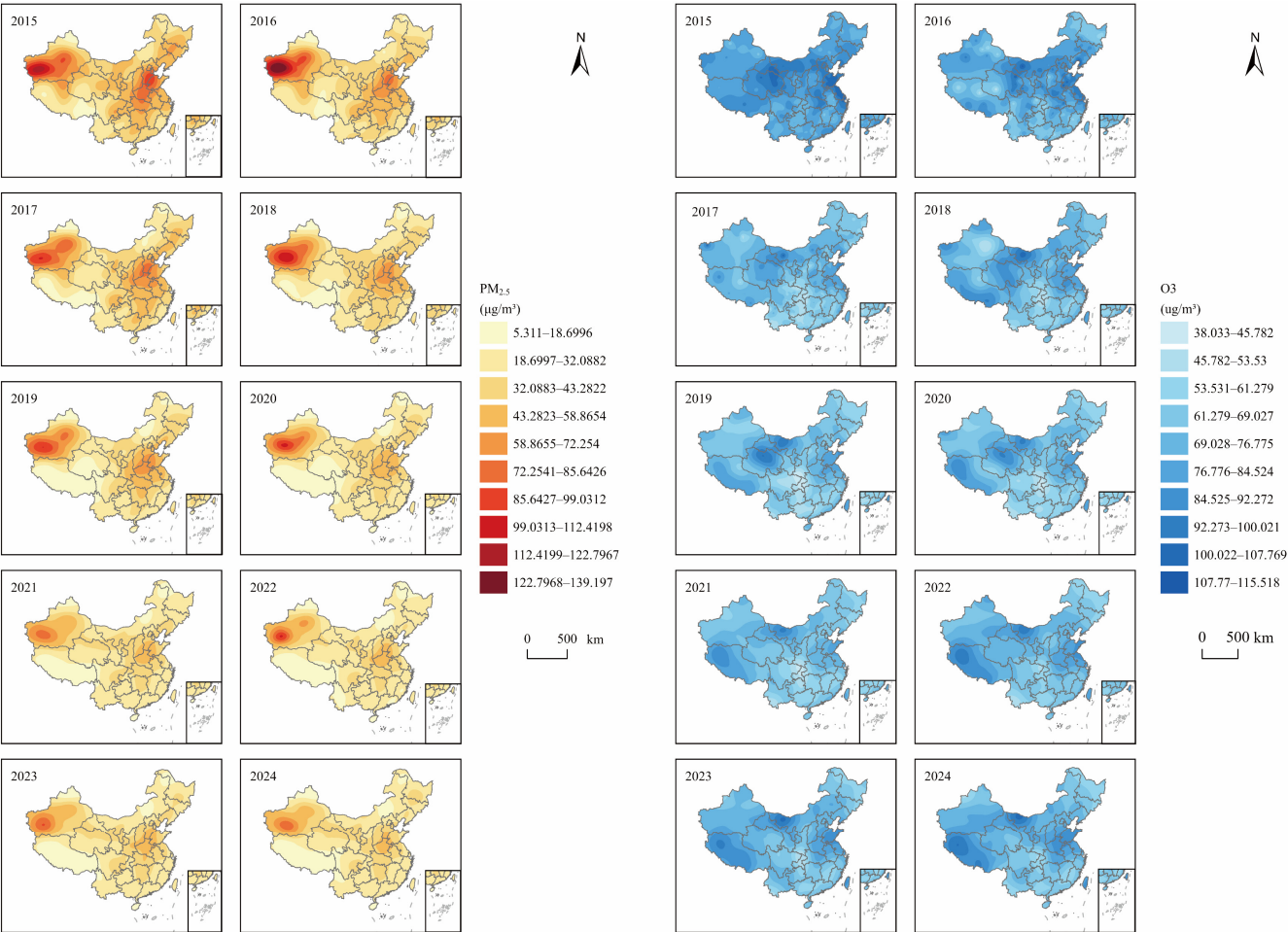


Figure 2. Annual mean concentrations of PM_{2.5} and O₃ in China from 2015 to 2024 (µg/m³).

The mean annual reductions in air pollutants across 31 provincial-level regions in mainland China from 2015 to 2024 are summarized in Table S2. Henan Province recorded the highest annual mean concentration of PM_{2.5} (56.96 µg/m³), while Xinjiang Uygur Autonomous Region exhibited the highest PM₁₀ level (118.41 µg/m³). The highest annual mean concentrations of SO₂ (26.95 µg/m³) and CO (1.07 mg/m³) occurred in Shanxi Province, and Tianjin showed the highest NO₂ concentration (39.26 µg/m³). Shandong Province reported the highest O₃ level (84.95 µg/m³).

Conversely, the Tibet Autonomous Region, characterized by its high-altitude, recorded the lowest annual mean concentrations of PM_{2.5} (17.03 µg/m³), PM₁₀ (36.27 µg/m³), and NO₂ (16.93 µg/m³). Tianjin exhibited the largest reductions in CO (59.8%) and PM_{2.5} (51.83%), while Beijing recorded the largest decline in NO₂ (45.12%). Shanghai experienced the greatest decrease in O₃ (26%), and Tibet showed the greatest reductions in PM₁₀ (54.18%). Among all the provinces, Shanxi achieved the most substantial decline in SO₂ (84.61%).

3.2. Prediction Results

To evaluate model performance across diverse regional conditions, one representative city was randomly selected from each of the seven major geographical regions—Jinzhou, Changzhi, Zhengzhou, Guilin, Jinan, Urumqi, and Panzhihua. Independent datasets from these cities were used to train and test the RNN, LSTM, and CNN-LSTM models and the predicted concentrations were compared against observed values. The corresponding model mean evaluation metrics are provided in Table 3.

Table 3. Mean performance evaluation metrics of the prediction models for the seven representative cities.

Model	Mean RMSE	Mean MAE	Mean R ²
RNN	1.852	0.976	0.990
LSTM	1.802	0.915	0.990
CNN-LSTM	2.344	1.040	0.985

All three deep learning models demonstrated strong predictive capability for most pollutants, with generally low error metrics. Among them, the LSTM model achieved the highest overall accuracy, particularly for CO, SO₂, and NO₂, yielding mean RMSE and MAE values of 1.802 and 0.915, respectively. These results slightly outperformed the RNN (mean RMSE = 1.852, mean MAE = 0.976) and CNN-LSTM (mean RMSE = 2.344, mean MAE = 1.040) models. Notably, CO exhibited the most accurate predictions across all models, with R² values exceeding 0.99 and markedly lower RMSE and MAE compared to other pollutants (Figure 3). O₃ predictions showed greater uncertainty, with R² values below 0.975, and RMSE exceeding 6.115 (Figure 4). For PM₁₀, the LSTM model demonstrated the most pronounced advantage in prediction accuracy, achieving an R² value approaching unity (0.999).

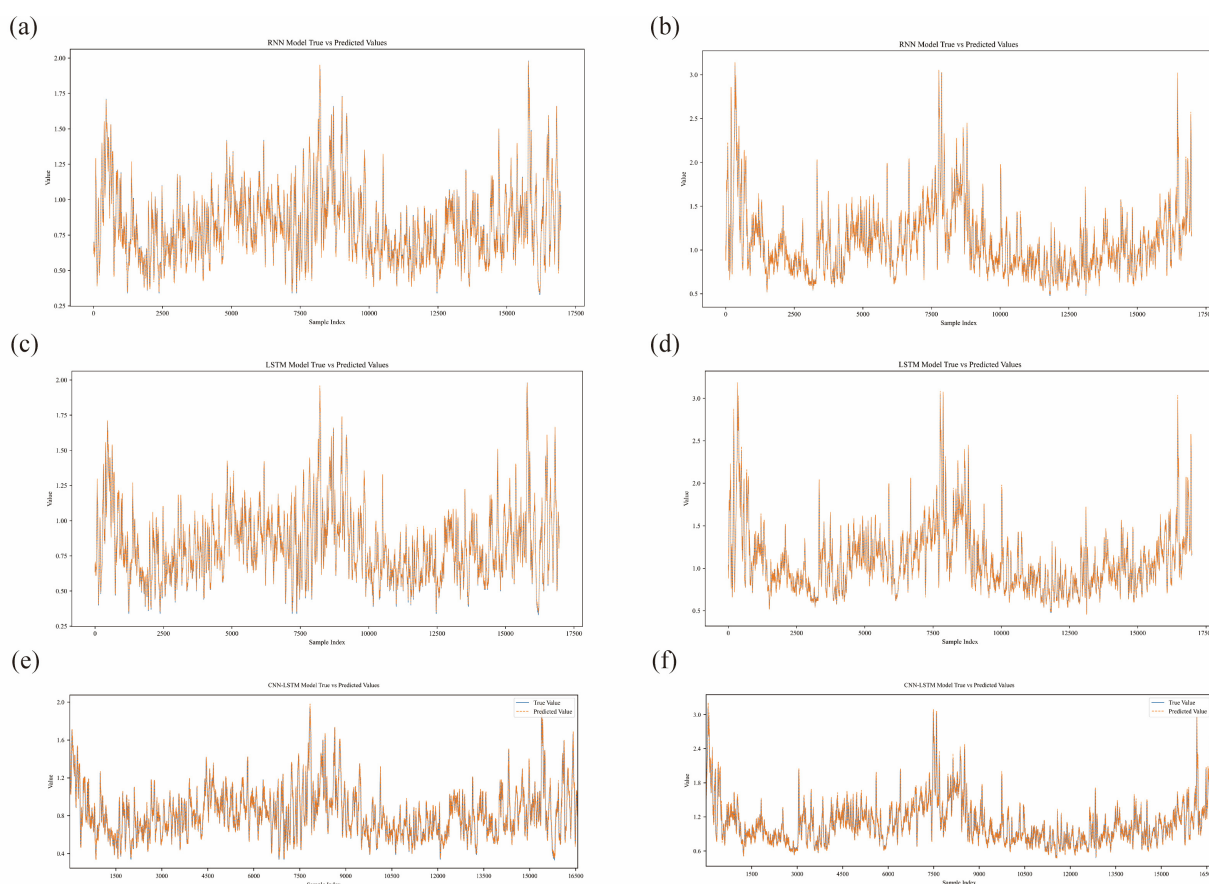


Figure 3. Comparison between observed and predicted CO concentrations across representative cities using three deep learning models. (a,c,e) Changzhi; (b,d,f) Panzhihua.

These findings revealed significant regional variations in model performance (Table S1). In Guilin, all models produced consistently accurate pollutant concentration predictions, with minimal variation among models. In contrast, predictive accuracy for SO₂ in Urumqi markedly declined, as reflected by the relatively low R² values for the RNN (0.961), LSTM (0.959), and CNN-LSTM (0.909) models. Substantial variation in model performance was also observed for PM₁₀ in Changzhi. The LSTM model achieved near-perfect predictive accuracy (RMSE = 1.313, R² = 0.999), with errors significantly lower than those of the RNN (RMSE = 4.023, R² = 0.993) and CNN-LSTM (RMSE = 4.476, R² = 0.991) models.

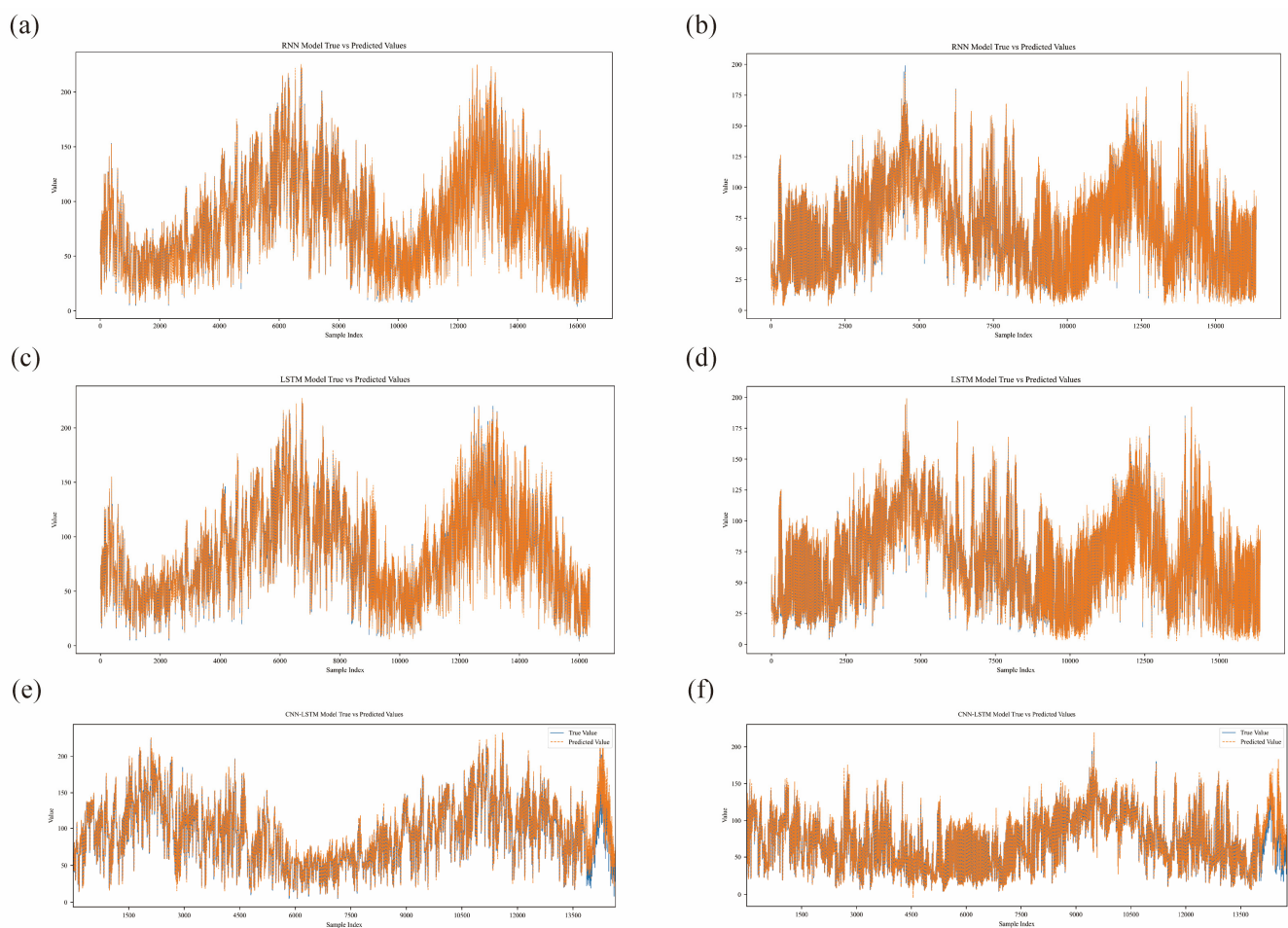


Figure 4. Comparison between observed and predicted O₃ concentrations across representative cities using three deep learning models. (a,c,e) Changzhi; (b,d,f) Panzhihua.

4. Discussion

Air quality in China has significantly improved over the past decade, reflecting the effectiveness of national air pollution prevention and control policies. However, the improvement rates varied considerably across pollutants and regions, underscoring the complexity of air quality management and the persistence of emerging challenges. Although the RNN, LSTM, and CNN-LSTM models all exhibited strong fitting and predictive capabilities, their performance was not entirely consistent. Differences in model architecture, pollutant characteristics, and regional geographic conditions were found to substantially influence prediction accuracy.

From 2015 to 2024, the annual mean concentrations of major air pollutants in China exhibited an overall downward trend. The most pronounced decline occurred in SO_2 [21], primarily due to widespread fuel desulfurization and strengthened industrial emission controls implemented under successive national air pollution prevention action plans. Temporary rebounds in particulate matter and NO_2 concentrations were recorded during 2016–2017 and 2022–2023, likely associated with fluctuations in socioeconomic activity—particularly the resumption of industrial operations following the relaxation of COVID-19 containment measures in late 2022 [4]. Furthermore, interannual pollutant concentrations can be substantially influenced by meteorological variability through boundary layer height, wind speed and direction, precipitation scavenging, atmospheric stability, and regional transport. Stable boundary layers and weak winds favor particulate matter accumulation, whereas higher temperature and stronger solar radiation may accelerate photochemical O_3 formation [31]. These variations align closely with implementation timelines of key national policies, such as the Three-Year Action Plan and Air Quality Sustained Improvement Action Plan, underscoring their effectiveness in reducing emissions.

Although NO_x and VOCs reduction measures implemented under the Three-Year Action Plan (2018–2020) have mitigated O_3 increases [32], O_3 remains a growing management concern, as the apparent decrease in O_3 over the full 2015–2024 interval is reflected as the relative change between the start and end years rather than a persistent monotonic improvement. Rising temperatures, intensive vehicle activity, petrochemical VOC emissions, and nonlinear VOC- NO_x chemistry may jointly exacerbate O_3 pollution [33]. Consequently, controlling O_3 formation is expected to be a central focus in the next phase of China's air quality management.

Spatially, the distribution of high pollutant concentrations exhibited strong regional consistency. North China experienced the steepest declines in particulate matter, SO_2 , NO_2 , and CO levels, reflecting both its historically high emissions and the effectiveness of control measures in regions with dense populations, energy-intensive industries, and heavy fossil fuel use. East China emerged as the primary O_3 pollution hotspot, driven by intensive transportation activity and high VOC emissions from industrial sources. In contrast, Southwest and South China generally maintained lower pollutant concentrations [21], benefiting from favorable atmospheric dispersion conditions and lighter industrial loads. Xinjiang Uygur Autonomous Region recorded the highest annual mean PM_{10} concentration, influenced by natural dust transport from the Taklamakan Desert and land reclamation in oasis areas. Implementing a dust-source attribution and deduction mechanism is recommended to more accurately assess anthropogenic emission outcomes. Although Shanxi Province—China's traditional coal energy base—achieved the largest relative decline in SO_2 , its absolute concentrations remained the highest nationwide due to concentrated emissions from coking and chemical industries [23], highlighting the need for structural energy transformation. Tibet Autonomous Region consistently exhibited the lowest concentrations of $\text{PM}_{2.5}$, PM_{10} , and NO_2 , owing to limited anthropogenic activity and high-altitude geography. These characteristics make Tibet a valuable background reference area for assessing China's ambient air quality.

Regional disparities in emission reduction rates across pollutants revealed differences in the effectiveness of air quality control measures. North China achieved the greatest reductions in $\text{PM}_{2.5}$, SO_2 , and CO concentrations, underscoring the effectiveness of the joint prevention and control initiatives implemented in the “2 + 26” key cities. In contrast, Northwest China showed minimal declines in particulate matter, likely due to substantial natural dust contributions and the limited representativeness of its sparse monitoring network [24]. The findings highlight the need for improved source apportionment and more targeted management of anthropogenic emissions. Notable reductions in $\text{PM}_{2.5}$ in Tianjin

and Beijing further reflect their leadership in optimizing energy use and transportation systems [34].

For PM_{2.5}, continuous reductions in coal combustion, industrial emissions, fugitive dust, and heavy-duty diesel emissions are still required in North China and Northwest China. For O₃, priority should be given to the coordinated control of VOCs and NO_x, especially from mobile sources, petrochemical industries, solvent use, airports and logistics hubs [35]. In 2024, the annual average concentrations of SO₂, NO₂, PM_{2.5}, and PM₁₀ all met the National Ambient Air Quality Standard Grade II limits, indicating that through the continuous implementation of the Air Pollution Prevention and Control Action Plan and subsequent policies, air quality has achieved significant improvement in China [36]. The concentrations of the four major pollutants satisfy the basic requirements of Class II functional areas, including residential zones, commercial and transportation mixed areas, cultural zones, industrial zones, and rural areas. This outcome is consistent with the nationwide trend of continuous air quality improvement reported by the Ministry of Ecology and Environment.

The concentration-based monitoring results should be interpreted in conjunction with the Air Quality Index (AQI), which is the predominant metric utilized for public health purposes. Conceptually, the AQI calculation is based on a maximum sub-index formulation, where the aggregate score is defined exclusively by the highest Individual Air Quality Index among the dominant primary pollutants. Consequently, while long-term reductions in individual criteria pollutants generally align with improved AQI (Figure S5), this composite index often obscures the distinct spatiotemporal dynamics and exposure profiles of each pollutants. Relying exclusively on the aggregate AQI limits the diagnostic capacity to identify which specific pollutant species requires urgent source-tailored mitigation. Therefore, robust policy formulation necessitates a paradigm that integrates aggregate indices with pollutant-specific mass concentration analyses.

The LSTM model demonstrated the highest predictive performance across most pollutants, characterized by strong fitting accuracy, stability, and generalization ability [20]. Its superior performance primarily arises from its gating mechanism, which effectively captures long-term dependencies in time series data and mitigates the vanishing gradient problem. In comparison, although the RNN offers a simpler architecture and higher computational efficiency, its limited capacity to model long sequences resulted in slightly lower prediction accuracy. The CNN-LSTM model performed less effectively for certain pollutants, producing significantly higher errors than LSTM. This may be attributed to its greater model complexity, which increases the risk of overfitting during training, and to the convolution layers extracting local features that introduce noise unrelated to long-term pollutant trends, thereby reducing overall predictive performance.

Pollutant type significantly influenced model prediction performance. All models achieved the highest accuracy for CO, likely due to its stable chemical properties, simpler emission sources, and regular temporal patterns, which facilitate model learning. Conversely, O₃ prediction exhibited higher errors [20]. As a secondary pollutant, O₃ formation involves complex photochemical reactions and nonlinear interactions influenced by precursor concentrations and meteorological conditions, increasing prediction uncertainty. Incorporating additional environmental variables in future studies could improve prediction capability for complex pollutants like O₃.

Model prediction performance exhibited notable regional variation. Predictions in Guilin were generally more accurate, with minimal differences between models, likely owing to lower pollution levels and favorable meteorological conditions that enhanced model generalization. In contrast, SO₂ predictions in Urumqi markedly declined across all models, influenced by seasonal heating, intensive industrial emissions, and frequent sandstorms, which increased time series noise and non-stationarity. In Changzhi, the LSTM

model outperformed others for PM₁₀ prediction, whereas CNN-LSTM performed poorly, highlighting that more complex model combinations do not necessarily improve accuracy [37]. Local spatiotemporal heterogeneity in pollutant sources may limit composite models' ability to capture key patterns effectively. Consequently, selecting simpler models with higher training efficiency may be a more cost-effective approach when accuracy is sufficient.

This study has several limitations that warrant consideration in future research. First, data from urban air quality monitoring stations offer limited coverage of rural, remote, and industrial peripheral areas, which may affect Kriging accuracy and regional averages, especially in Northwest China. Future monitoring networks should integrate reference-grade stations, satellite products, chemical transport models, and calibrated low-cost sensors. Second, while the study focused on long-term trends, it did not explicitly account for the influence of meteorological variability on pollution trends. Future work should employ statistical models to quantify the relative contributions of emissions and meteorological factors. Third, by relying on annual mean concentrations, the analysis failed to capture seasonal pollution patterns or extreme pollution events. Subsequent studies should investigate episodic pollution processes and assess the potential impacts of energy transitions under China's "dual carbon" goals.

5. Conclusions

From 2015 to 2024, air quality in China improved significantly, with annual mean concentrations of six criteria pollutants generally declining, reflecting the effectiveness of national air pollution control policies under the three Air Pollution Prevention and Control Action Plans. Distinct regional variations in pollutant distributions underscore the need for region-specific control strategies, particularly for targeted O₃ mitigation. Among the predictive models evaluated, LSTM demonstrated superior accuracy, stability, and generalization compared to RNN and CNN-LSTM, providing robust technical support for precise, region-specific air quality management.

By examining air pollution from holistic, regional, and long-term perspectives, this study systematically characterized spatial disparities, temporal trends, and policy impacts across China. By integrating environmental science, Geographic Information Systems (GIS), and deep learning, this study advances the theoretical understanding of air pollution dynamics while providing interdisciplinary tools for addressing complex environmental health challenges.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/atmos17070659/s1>, Figure S1: Annual mean concentrations of NO₂ in China from 2015 to 2024 (µg/m³); Figure S2: Annual mean concentrations of PM₁₀ in China from 2015 to 2024 (µg/m³); Figure S3: Annual mean concentrations of SO₂ in China from 2015 to 2024 (µg/m³); Figure S4: Annual mean concentrations of CO in China from 2015 to 2024 (mg/m³); Figure S5: Annual mean AQI levels in China from 2015 to 2024; Table S1: Annual mean values (mg/m³ for CO and µg/m³ for other pollutants) of air pollutants; Table S2: Reduction (%) in air pollutants in 31 provincial-level regions from 2015 to 2024; Table S3: Performance Evaluation metrics of the prediction models for the seven representative cities.

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