Surface Ozone in the Central Plains Urban Agglomeration, China: Spatial-Temporal Variations and Health Impacts

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Abstract

To investigate the spatial-temporal variations and health impacts of O₃ (ozone) in the Central Plains Urban Agglomeration, China (CP-UA), multiple and transdisciplinary methods were employed to analyze the collected millions of O₃ concentrations data. The results showed that the annual average concentration of O₃ in the CP-UA reduced by 19.7% from 2017 to 2020. O₃ monthly concentrations exhibited a multimodal structure and a feature of “high in summer and winter, low in spring and autumn”. In spatial distribution, the main distribution of O₃ concentration was aligned in the northwest-southeast direction in the CP-UA. O₃ concentrations displayed positive spatial autocorrelations. The most polluted cities were distributed in northern CP-UA, forming a high-high (HH) agglomeration of O₃ concentrations. Cities in southern CP-UA had low O₃ concentrations, forming a low–low (LL) agglomeration pattern. It was estimated that the premature mortalities attributed to O₃ for respiratory disease in warm months were 15,960 per year. The premature mortalities decreased by 28.7% in 2020 compared to 2017. The rescaled range analysis suggested a declining trend of O₃ concentrations and premature mortalities in the CP-UA.

Keywords: ozone, central plains urban agglomeration, spatial-temporal variations, health impacts

Introduction

With the rapid economic development, industrial expansion, and urbanization over the past decades, China has experienced serious O₃ (ozone) pollution, which has attracted much attention from the public, government, and researchers [1-4]. O₃ is secondary air pollution attributed to the photochemical reactions between nitrogen oxides (NOₓ) and volatile organic compounds (VOCs) under solar radiation [3]. Motor vehicles and industrial activities are the main sources of O₃ precursors [5]. High concentrations of ozone can cause heavy smog in metropolitan cities, harm human health, and affect crop yield [6, 7]. From 2013 to 2016, surface O₃ concentrations have increased by
10.8% in China [8]. The increasing O₃ concentrations caused hundreds of thousands of premature mortalities [9], millions of metric tons of losses of key crops [6], and billions of dollars in economic losses [10]. O₃ has become the second most important air pollutant after PM$_{2.5}$ in most cities of China.

Recently, extensive studies focused on urban agglomerations in China such as Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Pearl River Delta (PRD) [10-14], to clarify the ozone spatiotemporal variations, regional transportations, and health impacts. The results demonstrated that the surface O₃ concentrations in megacities of China (e.g. Beijing, Shanghai, and Shenzhen) were much higher than the World Health Organization Standard (maximum daily 8-h average (MDA8) O₃ >50 ppbv). As production of photochemical reactions, O₃ formation regimes relating to weather conditions, terrain, and precursors [16], leads to the different spatiotemporal patterns of O₃ among urban agglomerations. To our best knowledge, only a few studies focused on the regional O₃ pollution in the Central Plains Urban Agglomeration (CP-UA). CP-UA is the largest urban agglomeration in Central China, including 30 prefecture-level cities with a population of more than 160 million. CP-UA is seriously constrained by resources and population agglomeration [17], causing high levels of PM$_{2.5}$ and O₃ [18]. All cities in Henan Province belong to the CP-UA. Zhengzhou, the capital city of Henan province and the regional central city of the CP-UA as well, was seriously O₃ polluted [19, 20], increasing the mortality risk of cardiovascular and respiratory [21]. Other cities in the CP-UA, e.g. Xingtai, Handan, Anyang, Jiaozuo, Pingdingshan, Liaocheng, and Yuncheng were characterized by industry or energy-consuming, which emitted a large amount of O₃ precursors and suffered serious O₃ pollution. Previous studies found that in Henan Province, due to O₃ pollution, the annual mean relative yield loss of wheat was 8.8%-14.1% [22], and the premature mortalities caused were about 7000 [23]. Therefore, deep and comprehensive research on surface O₃ in the CP-UA is necessary.

The present study aims to investigate the spatiotemporal variations and health impacts of ozone in the CP-UA by using multiple and transdisciplinary methods. Specifically, we (1) systemically characterize the annual, seasonal, monthly, and diurnal variations of ozone concentrations, (2) analyze the spatial patterns and variations of ozone, and (3) estimate the premature mortality attributed to O₃ exposure. Our findings are conducive to improving the understanding of the spatiotemporal patterns and the mechanisms of O₃ pollution in the CP-UA. Meanwhile, the findings provide scientific support for determining the efficient approach for O₃ reduction in CP-UA.
Materials and Methods

Study Area

The CP-UA (31.4°N-37.8°N, 110.2°E-118.2°E) is located in central China (Fig. 1), including 30 cities: all 18 cities in Henan Province, Changzhi, Jincheng, and Yuncheng in Shanxi Province; Liaocheng and Heze in Shandong Province; Huaibei, Bengbu, Suzhou, Fuyang, and Bozhou in Anhui Province; and Xingtai and Handan in Hebei Province [24]. The CP-UA covers 287,000 km² with a population of more than 160 million.

Materials

A long time series of hourly concentrations of O₃ from January 2017 to December 2020 in the CP-UA were obtained from the national air quality monitoring network operated by China National Environmental Monitoring Center. Due to the absence of air quality monitoring site in Jiyuan, O₃ data was lacking. O₃ concentration was measured by Ultraviolet photometer or Differential Optical Absorption Spectroscopy. The instrumental operation, maintenance, and quality assurance/quality control are conducted according to the China Environmental Protection Standards “HJ 818-2018”. We used O₃ daily maximum 8-hour sliding average (MDA8-O₃) concentration as the O₃ level of that day and used the 90th percentile of MDA8-O₃ as the annual assessment standard [25]. In this study, the seasonal, monthly (spring: March to May, summer: June to August, autumn: September to November, winter: January, February, and December), and daily variations of O₃ were calculated using the mean of the MDA8-O₃ in each city. The diurnal variations of O₃ concentrations were calculated using the hourly O₃ concentration of each city.

Methods

Kernel Density Estimation

Kernel density estimation was employed to calculate the O₃ density function, which is defined as:

\[ f(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left( \frac{x_i - x}{h} \right) \]

where \( n \) is the number of samples, \( h \) indicates the bandwidth, and \( K \) represents the kernel weighting function. In the present study, the Epanechnikov kernel and Silverman’s bandwidth were used [26].

Standard Deviational Ellipse

The standard deviation ellipse (SDE), namely directional distribution [27], demonstrates elements in the main distribution area through four key parameters, i.e., center point, major axis, minor axis, and azimuth. The mean center is the central location for the entire dataset. The major and minor axes of the ellipse suggest the direction and range of the data distribution, respectively [28]. Azimuth defines the main trend direction. In this paper, the spatial feature of ozone in the CP-UA was identified by SDE. The main parameters of SDE are calculated as follows:

Mean Center:

\[ x_{mc} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \]  
\[ y_{mc} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \]

where \( x_i \) and \( y_i \) are the coordinates for \( i \), \( w_i \) represents the weight value, and \( n \) is equal to the total number of sites.

The angle of rotation is calculated as:

\[ \tan \theta = \frac{A+B}{C} \]

\[ A = (\sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} y_i^2) \]

\[ B = \sqrt{\left(\sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} y_i^2\right)^2 + 4\left(\sum_{i=1}^{n} x_i y_i\right)^2} \]

\[ C = 2\sum_{i=1}^{n} x_i y_i \]

where, \( x_i \) and \( y_i \) indicate the deviation of the \( x \)-\( y \)-coordinates from the Mean Center.

The standard deviations for the \( x \)-axis and \( y \)-axis are:

\[ \sigma_x = \sqrt{\frac{\sum_{i=1}^{n} (x_i \cos \theta - y_i \sin \theta)^2}{n}} \]

\[ \sigma_y = \sqrt{\frac{\sum_{i=1}^{n} (x_i \sin \theta - y_i \cos \theta)^2}{n}} \]

Rescaled Range (R/S) Analysis

In this paper, the R/S analysis was employed to discuss the changing trend of O₃ concentration. The R/S analysis proposed by Hurst [29], is the ratio between range and standard deviation, which is calculated as follows [30]:

\[ x(j) = \frac{\sum_{i=1}^{n} x_i}{j}, \quad j = 1, 2, 3, \ldots \]

\[ R(j) = \max_{1 \leq i < j} x(i,j) - \min_{1 \leq i < j} x(i,j), \quad j = 1, 2, 3, \ldots \]

\[ R(j) = \max_{1 \leq i < j} x(i,j) - \min_{1 \leq i < j} x(i,j) \]

\[ j = 1, 2, 3, \ldots \]
\[ S(j) = \left[ \frac{1}{2} \sum_{i=1}^{j} (x(i) - \bar{x})^2 \right]^{1/2}, \quad j = 1, 2, 3, \ldots \] (13)

where \( x(i) \), \( x(i,j) \), and \( S(j) \) are the mean, cumulative dispersion, range, and standard deviation of the given time series, respectively. If \( x \) is a random sequence, then:

\[ \frac{R(j)}{S(j)} = \left\{ \frac{\sigma}{2} \right\}^H \] (14)

where \( H \) indicates the Hurst index of the time series.

The \( H \) value ranges from 0 to 1. If \( H = 0.5 \), it indicates that the O3 time series is random and there is no long-term relationship; If \( 0.5 < H < 1 \), it suggests that the O3 time series has long-term persistence. The change in O3 concentration in the future is consistent with the change trend in the past. The closer \( H \) is to 1, the stronger the persistence; If \( 0 < H < 0.5 \), it represents the O3 time series is anti-sustainability. The change in O3 concentration in the future is opposite to the change trend in the past. The closer \( H \) is to 0, the stronger the anti-sustainability.

**Global and Local Spatial Autocorrelation Analysis**

The spatial distributions of O3 concentrations are related to spatiotemporal and geospatial processes. Therefore, the global Moran's I index was employed to quantitatively determine the global autocorrelation of O3 in the CPUA. Detailed descriptions for the global Moran's I can be found in previous studies [31, 32]. The global Moran's I ranges from 0 to 1. A negative (positive) index suggests a negative (positive) correlation and the smaller (greater) the index, the stronger the spatial dispersion (agglomeration) of O3, while an \( I_{\text{global}} \) of 0 indicates no spatial autocorrelation.

Global spatial autocorrelation can only judge whether the geographical variables have spatial autocorrelation but cannot reflect the characteristics of an urban spatial agglomeration within a region [17]. Therefore, the local Moran's I index was used to identify the distribution and agglomeration patterns of O3 in the CPUA. Based on the calculated local Moran's I index, the spatial association modes can be classified into four types [33]: high-high clustering type (hereinafter HH), low-low clustering type (LL), low-high clustering type (LH), and high-low clustering type (HL). The index that fails the significance test is classified as not significant.

**Human Health Impacts**

High O3 concentration can cause respiratory diseases, and the premature mortality attributed to O3 exposure is estimated as formulas [34]:

\[ \Delta M = y_o N(RR - 1)/RR \] (15)

where \( \Delta M \) represents the excess mortalities attributable to O3 exposure, \( y_o \) is the baseline mortality rate, \( N \) indicates the exposed population, and \( RR \) is the relative risk. \( RR \) is calculated by:

\[ RR = \exp(\beta(C - C_o)) \] (16)

where \( \beta \) denotes the concentration-response coefficient, \( C \) and \( C_o \) represent O3 concentration and reference concentration, respectively.

In this study, the population data are from the seventh population census of China. The mortality rate for respiratory disease during 2017-2020 is collected from China Statistical Yearbook issues 2018, 2019, 2020, and 2021 (http://www.stats.gov.cn/tjsj/ndsj/), which is 67.2, 68.02, 65.02, and 55.36, respectively. The \( RR \) is 1.04, a 20 \( \mu \)g/m\(^3\) increase in MDA8-O3 concentration is associated with a 4% increase in \( RR \) of death from respiratory disease, and the recommended value of \( C_o \) is 75.2 \( \mu \)g/m\(^3\) [34].

**Results and Discussion**

**Temporal Variations in O3 in the Central Plains Urban Agglomeration**

**Annual Variation**

Fig. 2 shows the estimated kernel density and over-standard rates of the O3 concentrations in the CP-UA from 2017 to 2020. Overall, the annual average concentration of O3 (90th percentile of MDA8-O3) in the CP-UA was gradually reduced from 2017. Specifically, in 2020 the yearly average O3 concentration amounted to 203.6 \( \mu \)g/m\(^3\), and was reduced by 19.7% relative to that in 2017 (253.6 \( \mu \)g/m\(^3\)). As displayed in Fig. 2a), the peak of the kernel-density curves became steeper and moved to the left from 2017 to 2020, which indicated that O3 concentrations in most of the cities of the CP-UA were continuously reduced. The upper tail of the density curves decreased over time, suggesting that cities with high O3 concentrations (more than 250 \( \mu \)g/m\(^3\)), had substantial decrease in O3 concentration. In 2017 the number of cities with annual O3 concentrations greater than 220 \( \mu \)g/m\(^3\) was 24, while the number decreased to 2 in 2020. As shown in Fig. 2b), the proportion of MAD8-O3 exceeded the China National Ambient Air Quality Standards I (CAAQS grade I; 100 \( \mu \)g/m\(^3\)) in CP-UA over 2017-2020 was 81.6%. And the proportions exceeded the Grade 2 limit (160 \( \mu \)g/m\(^3\)) and Grade 3 limit (250 \( \mu \)g/m\(^3\)) was 39.3%, indicating severe O3 pollution. The proportion that exceeded the Grade 2 limit during 2017-2020 was 44.3%, 42.5%, 41.0%, and 29.3%, respectively, suggesting the reduction of O3 pollution in the CP-UA. In other urban agglomerations of China, e.g., BTH, PRD, and YRD, O3 concentrations also decreased from 2017 to 2020 [35], which indicated the Air Pollution Prevention
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and Control Action Plan formulated by China government worked as intended.

Monthly Variation

The monthly characteristics of O₃ concentrations in the CP-UA over 2017-2020 are illustrated in Fig. 3a). Previous studies have pointed out that monthly variation characteristics in O₃ are related to latitude in China. The unimodal structure is generally found for latitudes over 35°N, whereas the bimodal structure is in most of the cases identified south of 35°N [36]. CP-UA covers a latitude of 31.4°N-37.8°N. A multimodal structure of O₃ monthly variation was found in CP-UA in this study. The monthly average O₃ concentrations showed an increasing trend from February to June, a decreasing trend from July to October, and an increasing trend in November and December. The highest monthly average concentrations occurred in June, with 195.5 μg/m³. As displayed in Fig. 3b), the seasonal averages of the O₃ concentrations in the CP-UA during 2017-2020 in spring, summer, autumn, and winter were 149.8, 171.2, 131.1, and 160.0 μg/m³, respectively. The O₃ concentrations showed a feature of “high in summer and winter, low in spring and autumn” in the CP-UA, which is different from the feature of “high in spring and summer, low in autumn and winter” in the YRD [35]. The meteorological conditions are the important factor that influences the monthly variation of O₃ in the CP-UA. In summer, the relatively high temperature and strong radiation enhance the photochemical reactions, which leads to increased O₃ production. In winter, most regions in China have the lowest O₃ levels [35, 36], while a high O₃ concentration was observed in the CP-UA in this study. An increasing winter-spring O₃ and increasing association of high ozone with winter haze events were found in the North China Plain [39]. We inferred that the high-level O₃ in winter in the CP-UA may be related to PM₂.₅ concentration. The collaborative governance of PM₂.₅ and O₃ become an important issue in the CP-UA.

Diurnal Variation

As the photochemical reactions product, O₃ concentrations are closely related to solar radiation. As shown in Fig. 4, The diurnal variation of O₃ concentrations exhibited a unimodal character in the CP-UA, with high O₃ concentrations in the daytime and low in the nighttime, which is consistent with other regions of China [40]. In the daytime, with the sun rising and solar radiation enhanced, anthropogenic precursors such as VOCs and NOₓ participate in photochemical reactions and promote the formation of O₃ [41].
The O₃ concentration increased during 8:00~16:00 (LST) and reached a maximum value of 116.1 μg/m³ at 16:00 (Fig. 4b). Then the O₃ concentration decreased continually. During the night time, O₃ can be eliminated by NOₓ titration reactions. Recent studies suggested that particulate matter can also react with O₃ and eliminate it from the atmosphere [42]. In June and July, the O₃ concentration was still high at 20:00 (Fig. 4a). O₃ concentration above 150 μg/m³ lasted about 10 hours each day in June.

Spatial Distributions in O₃ in Central Plains Urban Agglomeration

Standard Deviational Ellipse Analysis

The overall variations in the spatial pattern of O₃ in the CP-UA in different years and seasons were characterized by SDE analysis. As displayed in Fig. 5a), the main distribution of O₃ concentration was aligned in the northwest-southeast direction in the CP-UA. The azimuth of the ellipse decreased from 123.2° in 2017 to 120.5° in 2020 (Table 1), which suggested the ellipse moved northward. The mean centers detected by SDE were located in northeastern Zhengzhou. From 2017 to 2020, the center of O₃ concentration across the CP-UA moved from 34.75°N, 114.05°E to 34.72°N, 114.09°E, which indicated a greater O₃ concentration decrease in northwestern CP-UA. The major axes of the ellipses increased from 211.6 to 220.5 km. The increase of the major axes illustrated the spatial aggregation tendency and the spatial changes in O₃ concentration from 2017 to 2020. The ratio between the major and minor axes of the ellipses presented an increasing tendency from 2017 to 2020, indicating the enhanced trend of directional distribution. As displayed in Fig. 5b), the seasonal variation of the standard deviation ellipse was more obvious than the annual variation. In summer and winter, the mean centers were located in Zhengzhou, and in spring and winter, the mean centers moved to Kaifeng. In winter, the major axes were the shortest (211.9 km) and the minor axes were the longest (176.3 km) in four seasons, and the ratio between the major and minor axes was lowest than in other seasons. This suggested that spatial dispersion of O₃...
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The spatial autocorrelation of O₃ concentrations was calculated to discuss the spatial correlation. As displayed in Fig. 6a), from 2017 to 2020, the annual Moran's I was 1.63, 1.85, 1.63, and 2.09, respectively, and all the values passed the significance test. The positive annual Moran's I suggested the positive spatial autocorrelation and the spatial agglomeration of O₃ concentrations in the CP-UA. This indicated that O₃ in a city can be affected by its neighboring cities. In a previous study, it was found that O₃ concentrations were spatially agglomerated in BTH and PRD, but spatially dispersed in Chengdu-Chongqing [35]. The highest global Moran's I in CP-UA was found in summer (2.59), indicating a strengthening agglomerated distribution of O₃ concentrations. We inferred that the photochemical reactions were strong in summer which lead to the formation and accumulation of O₃. Hence, regional cooperation across cities is necessary. To identify the distribution and agglomeration patterns of O₃ pollution in each city of CP-UA, local spatial autocorrelation analysis was employed in this study. As shown in Fig. 6b), the most polluted cities were distributed in northern CP-UA, forming a high-high (HH) agglomeration of O₃ concentration. The HH agglomeration cities including Xingtai, Handan, Changzhi, Liaocheng, Anyang, Jiaozuo, and Ximxiang are mostly industrial cities with intensive anthropogenic emissions and insufficient precipitation. Cities in southern CP-UA had low O₃ concentrations, forming a low-low (LL) agglomeration (Fig. 6b). The LL agglomeration cities included Zhoukou, Zhumadian, Xinyang, Fuyang, Bengbu, and Bozhou. Those cities are all located in the south of the North-South climatic transition zone, which means abundant precipitation. To sum up, O₃ control by any individual city was insufficient, and joint efforts across the CP-UA would be necessary to reduce regional O₃ pollution. More stringent measures should be taken in the northern CP-UA.

| Items | Variables | Parameters | Azimuth/degree | Mean center | Major axes/km | Minor axes/km | Area/km² |
|-------|-----------|------------|----------------|-------------|---------------|---------------|---------|
| Year  |           |            | 2017           | 123.20      | 114.05°E, 34.75°N | 211.6 | 176.3 | 117189 |
|       |           |            | 2018           | 125.41      | 114.08°E, 34.72°N | 211.3 | 175.8 | 116702 |
|       |           |            | 2019           | 125.19      | 114.10°E, 34.72°N | 207.9 | 179.1 | 117017 |
|       |           |            | 2020           | 120.53      | 114.09°E, 34.72°N | 220.5 | 176.1 | 121953 |
| Season| Spring    |            |                | 121.39      | 114.16°E, 34.71°N | 217.0 | 174.6 | 119008 |
|       | Summer    |            |                | 121.96      | 114.12°E, 34.76°N | 212.4 | 175.4 | 117026 |
|       | Autumn    |            |                | 124.15      | 114.22°E, 34.67°N | 217.2 | 175.1 | 119483 |
|       | Winter    |            |                | 118.81      | 114.09°E, 34.75°N | 211.9 | 176.3 | 117404 |

Table 1. Parameters of standard deviation ellipse in the Central Plains Urban Agglomeration.

Fig. 6. a) Global Moran's I index and b) spatial agglomeration of O₃ concentrations in the CP-UA in 2017-2020.
Human Health Impacts

To estimate O₃ impacts on health in the CP-UA, the premature mortality attributed to O₃ in warm months (from April to September) was calculated. As displayed in Fig. 7, from 2017 to 2020, the premature mortality related to O₃ for respiratory disease in the CP-UA was 17438, 17087, 16765, and 12549, respectively, which was...
much higher than in the YRD (5889 per year from 2015 to 2019) [34]. The reduction of premature mortalities in the CP-UA indicated that the measures taken by the Chinese government to control O₃ pollution have achieved good results. Among the 30 cities in the CP-UA, Zhengzhou was estimated to have the highest premature mortalities, with 1556, 1382, 1387, and 1110 cases in 2017, 2018, 2019, and 2020, respectively. Zhengzhou is the central city of the CP-UA, with a population of 12.6 million. The top ten cities with the highest premature mortalities, with 1556, 1382, 1387, and 174 cases in 2017, 2018, 2019, and 2020, respectively. We found that the population in some cities varies little, while the estimated premature mortalities vary largely. For example, the population of Xinyang and Xining were 6251929 and 6234401, respectively, and the premature mortalities were 668 and 480, respectively. This suggested that premature mortality is sensitive to O₃ concentration. As can be seen from Equation 16, premature mortality increase with O₃ concentration exponentially.

The time-series domain rescaling analysis method was employed to calculate the Hurst index of O₃ concentration in the CP-UA. As displayed in Fig. 8, the Hurst index ranged from 0.59 to 0.85, all larger than 0.5, indicating the time series of O₃ was long-term persistent, that is, the change in O₃ concentration in the future is consistent with the changing trend in the past. As discussed in the previous section, the O₃ concentration in the CP-UA from 2017 to 2020 was gradually reduced. This suggested that the O₃ concentration in the CP-UA will continue to decline in the future. Therefore, we inferred that the premature mortality attributed to O₃ in the CP-UA will continue to decline. Luoyang, Changzhi, Xining, Liaocheng, and Hebi ranked in the top 5 in terms of the Hurst index, which indicated that these cities are more likely to have a decline in O₃ concentration and premature mortality.

### Conclusion

In this study, multiple transdisciplinary methods, including geographical analysis and spatial statistics, were used to investigate the spatiotemporal distribution variations and the human health impacts of O₃ in the CP-UA. The results of the study showed that the annual average concentration of O₃ in the CP-UA reduced by 19.7% in 2020 compared to 2017. While, the proportion of MAD8-O₃ that exceeded the Grade 2 limit in 2020 was 29.3%, indicating still serious O₃ pollution. O₃ concentrations showed a multimodal structure trend with the month in the CP-UA, with the highest concentrations in June (195.5 μg/m³). The O₃ concentrations showed a feature of “high in summer and winter, low in spring and autumn” in CP-UA. In diurnal changes, O₃ concentrations exhibited an unimodal trend, with high in the daytime and low in the nighttime. Concerning spatial distribution, the main distribution of O₃ concentration was aligned in the northwest-southeast direction for the CP-UA. From 2017 to 2020, the centers of O₃ concentrations across the CP-UA moved southeast. In summer and winter, the mean centers were located in Zhengzhou, and in spring and winter the mean centers moved to Kaifeng. O₃ concentrations exhibited positive spatial autocorrelations in the CP-UA. The spatial autocorrelation was strongest in summer. The most polluted cities were distributed in northern CP-UA, including Xingtai, Handan, Changzhi, Liaocheng, Anyang, Jiaozuo, and Xining, forming a high-high (HH) agglomeration of O₃ concentration. Cities in southern CP-UA including Zhoukou, Zhumadian, Xining, Fuyang, Bengbu, and Bozhou, had low O₃ concentrations, forming a low-low (LL) agglomeration. According to our estimates, the premature mortality attributed to O₃ for respiratory disease in warm months was 15960 per year. The premature mortalities decreased by 28.7% in 2020 compared to 2017. Furthermore, the changing trend of O₃ concentration was predicted by rescaled range analysis. The calculated Hurst index of O₃ concentrations in all cities in the CP-UA was all larger than 0.5, indicating the declining trend of O₃ concentrations and premature mortalities in the CP-UA.

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### Conflicts of Interest

The authors declare no conflict of interest.

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