Investigating the biophysical and socioeconomic determinants of China tropospheric O₃ pollution based on a multilevel analysis approach

Su Ding · Jianhua He · Dianfeng Liu

Received: 6 May 2020 / Accepted: 15 December 2020 / Published online: 7 January 2021
© The Author(s), under exclusive licence to Springer Nature B.V. part of Springer Nature 2021

Abstract Severe tropospheric O₃ pollution has swept across China in recent years. Consequently, investigation of tropospheric O₃ concentration influencing mechanism is of significance for O₃ pollution control in China. Previous studies have rarely detected combined impacts of natural factors and anthropogenic activities behind tropospheric O₃ concentration in China at a national scale. Moreover, there is significant spatiotemporal heterogeneity of O₃ pollution distribution in China due to the temporal and

regional differences of socioeconomic and natural environmental condition in the vast territory. The targeted O₃ control recommendations for different regions and seasons should be put forward in terms of the spatiotemporal heterogeneity of O₃ concentration determinants. In this context, a three-level regression model integrating multi-scale biophysical and socioeconomic variables was proposed to explore the determinants of O₃ pollution in China. The results showed that the tropospheric O₃ concentration in the eastern and southeastern regions of China was strongly affected by meteorological conditions. In contrast, tropospheric O₃ pollution concentrated in inland areas

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10653-020-00797-8>.

S. Ding
School of Environmental and Resources Science,
Zhejiang A & F University, Hangzhou 311300, China
e-mail: suding12@foxmail.com

S. Ding
State Key Laboratory of Subtropical Silviculture,
Zhejiang A & F University, Hangzhou 311300, China

S. Ding
Key Laboratory of Carbon Cycling in Forest Ecosystems
and Carbon Sequestration of Zhejiang Province, Zhejiang
A & F University, Hangzhou 311300, China

S. Ding · J. He (✉) · D. Liu (✉)
School of Resource and Environmental Sciences, Wuhan
University, Wuhan 430079, China
e-mail: hjianh@whu.edu.cn

D. Liu
e-mail: liudianfeng@whu.edu.cn

J. He · D. Liu
Key Laboratory of Geographic Information System,
Ministry of Education, Wuhan University,
Wuhan 430079, China

mainly depended on the emission intensity from anthropogenic sources.

Keywords O₃ pollution · Multilevel regression analysis · Multiple determinants

Introduction

Tropospheric O₃ is one of the main air pollutants produced by photochemistry reaction under appropriate meteorology condition. With rapid industrial and economy development, the sharp increase in O₃ precursors emissions results in severe tropospheric O₃ episodes posing huge threat to human health and ecosystem productivity (Wang et al. 2017). Thousands of premature deaths are caused by high tropospheric O₃ exposure around the world each year (Cohen et al. 2017; Lelieveld et al. 2015). Furthermore, tropospheric O₃ is also phytotoxic for vegetation (Tai et al. 2014). Consequently, investigating the influencing mechanism of tropospheric O₃ concentration is urgent for O₃ episodes control. As a typical study area, China has experienced rapid industrialization and urbanization during the past 40 years of the reform and open-up policy. As an expense, tropospheric O₃ episodes have frequently emerged in the most regions of China in recent years, which have received much attention by scholars. The investigation aiming at exploring the influencing mechanism behind O₃ episodes at China national scale is essential. Notably, the regional difference of socioeconomic development is extremely prominent in China. The environmental pressure brought from socioeconomic activities varies from regions. The spatiotemporal variation in biophysical conditions also exerts different impacts on O₃ formation and diffusion. As a consequence, pollution control measures should be available for different regions and seasons across China.

In order to understand O₃ formation and influencing mechanism, scholars have conducted a large amount of research. Much research focuses on the complex reaction mechanisms among NO_x, VOCs and O₃. Chen et al. (2019) investigates O₃–NO_x–VOC sensitivity for identifying the VOCs and NO_x reduction ratio to control tropospheric O₃ pollution in Foshan City. Yang et al. (2019) analyzes the variation in the concentration of O₃, VOCs and NO_x in Wuhan City.

The exploration of VOCs impacts on photochemistry reaction, and main contributors to O₃ formation in Wuhan are also conducted. Furthermore, some scientific publications focus on O₃ sources apportionment. Li et al. (2019b) quantifies O₃ source apportionment by source regions and sectors in Yangtze River Delta (YRD) region. Shao et al. (2016) draws the conclusion that industry-related sources occupy the highest proportion of VOCs emission in YRD. Vehicular emission also contributes much to VOCs emission. Vegetation emission and liquefied petroleum gas/natural gas usage are also important VOCs sources in YRD. On the other hand, the research about O₃ concentration determinants has been carried out. Meteorological factors including temperature, relative humidity (RH), precipitation and planet boundary layer height (PBLH) are documented that they influence pollutant photochemistry and transmission directly or indirectly by many scholars (Gong et al. 2018; Hu et al. 2018; Sun et al. 2019). As the main atmospheric oxidant, the correlation between tropospheric O₃ and secondary aerosols has gained much attention as well (Li et al. 2019a; Zhang et al. 2018). The impacts of socioeconomic activities on tropospheric O₃ concentration also have been investigated (Huang et al. 2013; Li et al. 2019b).

As the literature review above shows, tropospheric O₃ pollution is a complex chemical process referring to anthropogenic and physical factors. As a consequence, the formulation of O₃ control measures should take various driving forces into consideration. Previous research focuses on O₃ formation and influencing mechanism in single scale of city or urban agglomeration to explore the biophysical and socioeconomic impacts separately, but seldom investigates the combined influences at national scale. Meanwhile, the single-level regression model is replaced with multi-level regression model in this study, since biophysical and socioeconomic influences are of significant scale effects. Meteorological conditions have monthly differences in the effects on O₃ pollution. For example, the variation in RH is abrupt in North China, with peak values of approximately 66% in July and the trough values of 45% during April (Si et al. 2018). In addition, Sun et al. (2019) uses sensitivity tests to demonstrate that meteorological conditions variations lead to significant changes in tropospheric O₃. Likewise, the influence of vegetation coverage on air quality mainly relies on the vegetation biomass which

has seasonal variation (Yang et al. 2015). The spatial heterogeneity of O₃ precursors emission results from the regional differences of anthropogenic activities (Li et al. 2019a). Besides, during the COVID-19 pandemic, industrial and vehicle emissions sharply decreased. However, severe air pollution episodes still emerged in most cities of China. It indicates that the short-term changes of socioeconomic activities have no significant influences on atmospheric environment. On the other hand, socioeconomic indicators always reflect annual activities, and the monthly and seasonal variability of biophysical influences was smoothed by statistical models integrating socioeconomic factors at annual level (Hao and Liu 2016; Liu et al. 2017; Zhan et al. 2018). Consequently, separately explaining the monthly, seasonal and regional variations in O₃ will help distinguish the spatiotemporal heterogeneity of determinants. In other words, the multilevel regression model can be used to explore the leading driving forces of O₃ concentration variation for every season and region.

The aim of this research is to explore the comprehensive and spatiotemporal heterogeneity determinants of tropospheric O₃ pollution in China. A three-level regression model was constructed to explore the spatiotemporal characteristics of O₃ pollution determinants, which will be helpful for developing differential pollution control measures in different regions. In the first level, monthly diurnal meteorological factors acted as the explanatory variables of monthly tropospheric O₃ pollution variation. The second level was used to explain the seasonal variation in O₃ concentration using seasonal average vegetation coverage. In the third level, socioeconomic annual impacts on O₃ concentration were uncovered in different regions. Finally, the targeted recommendations for O₃ pollution reduction in different regions and seasons could be put forwarded based on the outcomes of multilevel regression model.

The remainder of this paper is organized as follows. “Materials and methodology” section illustrates research data and the description of multilevel regression models. The outcomes of multilevel regression models and discussion are presented in “Results and discussion” and “Limitations and future work” sections. The final section provides the conclusions based on our results.

Materials and methodology

Data sources and processing

The data used in this research are shown in Table 1. Data from 353 cities which cover the seven regions suggested by Fang et al. (2017) in China were collected. The data describe the conditions of atmospheric environment and socioeconomic activities in China during 2015. Three pollutants concentration monitoring data, seven meteorology factors and ten socioeconomic data were collected. Specifically, the real-time monitoring data of O₃, PM_{2.5} and NO₂ were derived from 1490 national atmospheric monitoring sites (downloaded from China National Environmental Monitoring Center <http://www.cnemc.cn>) (Fig. 1) and we calculated the hourly arithmetic average of O₃ monitoring concentration in each month. Meanwhile, meteorology condition was described by MEERA-2 data. MERRA-2 reanalysis meteorological data (GMAO 2015a, b, c) were resampled into a grid at a spatial resolution of 0.1° using a bilinear algorithm further. Vegetation coverage is estimated by city area and FVC (fractional vegetation coverage) data (Li et al. 2017). The seasonal vegetation coverage in each city represents the whole vegetation coverage within prefecture-level city administrative boundaries. Socioeconomic data were extracted from the China city statistical yearbook (NBSC 2016a) reflecting socioeconomic activities in prefecture-level cities in China during 2015. Finally, we extracted the meteorological factors, vegetation coverage and socioeconomic indicators at air pollution monitoring stations. Real-time monitoring data and driving forces data were spatially and temporally matched to build multilevel models. Particularly, in this research, spring consists of March, April and May; summer spans from June to August; autumn falls in the months of September, October and November; and winter starts in December and ends in February.

Multilevel regression model design and specification

Figure 2 shows the processing of O₃ pollution influencing mechanism investigation. Before the modeling, several tests were employed to avoid spurious regression and multi-collinearity issues. The Kolmogorov–Smirnov normal distribution test was used

Table 1 Research data

Variables name	Abbreviation	Unit	Variables name	Abbreviation	Unit
O ₃ concentration	O ₃	μg m ⁻³	Population density	PD	person km ⁻²
Relative humidity	RH	%	Buses and trolley buses number	BN	Unit
Temperature	T	K	City paved roads area	CPRA	10 ⁴ sq m
Planetary boundary layer height	PBLH	m	Gross regional product per capita	PGRP	10 ⁴ yuan
Total precipitation	TP	kg m ⁻² s ⁻¹	Tertiary industry as percentage to GRP	TGRP	%
Zonal wind	ZW	m s ⁻¹	Residential gas consumption	GC	t
Meridional wind	MW	m s ⁻¹	Residential liquefied petroleum gas consumption	LPGC	t
Surface atmospheric pressure	AP	Pa	Gross industrial output value above designated size	GIO	10 ⁴ yuan
PM _{2.5} concentration	PM _{2.5}	μg/m ³	Industrial sulfur dioxide emission volume	ESO ₂	t
NO ₂ concentration	NO ₂	μg/m ³	Volume of industrial soot (dust) emission	EIS	t
Vegetation coverage	VC	km ²			

Fig. 1 Study area and monitoring station distribution

to examine the probability density distribution of O₃ concentration. This result led to the conclusion that O₃ concentration obeyed the positive skew distribution with a peak on the left of the median. Thus,

logarithmic transformation was adopted to covert O₃ concentration data into a normal distribution. Unit root and co-integration tests were performed to check the stationarity of independent variables. The results

Fig. 2 Flowchart of multilevel regression model analysis

showed that all independent variables were stable. Besides, with the application of VIF (variance inflation factor) calculation, the variables whose $VIF > 10$ were removed. We finally selected eight biophysical, two pollutants concentrations and ten socioeconomic variables. There was no multi-collinearity among these independent variables. Finally, a min–max normalization method was introduced to remove the unit of independent variables.

First, we built a null model to describe the spatiotemporal variances in the O_3 concentration quantitatively. There are no independent variables in the null model, and it takes the following form:

$$\text{Level I: } y_{ijk} = \alpha_{jk} + \varepsilon_{ijk} \quad (1)$$

$$\text{Level II: } \alpha_{jk} = \beta_k + u_{jk} \quad (2)$$

$$\text{Level III: } \beta_k = \gamma + v_k \quad (3)$$

where Eqs. (1)–(3) refer to the monthly, seasonal and annual variation concentrations of O_3 (α_{jk} , β_k and γ), respectively, and the random effects (ε_{ijk} , u_{jk} and v_k) vary among month, season and station. i , j and k represent the group code of the monthly, seasonal and annual levels, respectively.

A random intercept model is called as follows:

$$\text{Level I: } y_{ijk} = \alpha_{jk} + AX_{ijk} + \varepsilon_{ijk} \quad (4)$$

$$\text{Level II: } \alpha_{jk} = \beta_k^1 + BW_{jk} + u_{jk} \quad (5)$$

$$A = \beta^2 \quad (6)$$

$$\text{Level III: } \beta_k^1 = \gamma^1 + CZ_k + v_k \quad (7)$$

$$B = \gamma^2 \quad (8)$$

$$\beta^2 = \gamma^3. \quad (9)$$

Compared to null model, Eqs. (4)–(9) consider meteorological (X_{ijk}), vegetation (W_{jk}) and socioeconomic (Z_k) factors at different levels as explanatory variables that are multiplied by slope coefficients A (β^2 , γ^3), B (γ^2) and C , respectively.

Considering the random effect of the explanatory variables, the random slope model is expressed in the following form:

$$\text{Level I: } y_{ijk} = \alpha_{jk} + A_{jk}X_{ijk} + B_kW_{jk} + CZ_k + \varepsilon_{ijk} \quad (10)$$

$$\text{Level II: } \alpha_{jk} = \beta_k^1 + u_{jk}^1 \quad (11)$$

$$A_{jk} = \beta_k^2 + u_{jk}^2 \quad (12)$$

$$B_k = \beta_k^3 + u_{jk}^3 \quad (13)$$

$$C = \beta_k^4 + u_{jk}^4 \quad (14)$$

$$\text{Level III: } \beta_k^1 = \gamma^1 + v_k^1 \quad (15)$$

$$\beta_k^2 = \gamma^2 + v_k^2 \quad (16)$$

$$\beta_k^3 = \gamma^3 + v_k^3 \quad (17)$$

$$\beta_k^4 = \gamma^4 + v_k^4 \quad (18)$$

where the random influences of the explanatory variables on O_3 concentration are expressed by u_{jk}^2, u_{jk}^3 and u_{jk}^4 and v_k^2, v_k^3 and v_k^4 at seasonal and spatial levels, respectively. $A_{jk}(\beta_k^2, \gamma^2)$, $B_k(\beta_k^3, \gamma^3)$ and $C(\beta_k^4, \gamma^4)$ are the fixed coefficients expressing the monthly, seasonal and annual average influences on O_3 concentration, respectively. The seasonal and station random effects of O_3 concentration are noted using u_{jk}^1 and v_k^1 , respectively (Calvin 1994; Raudenbush and Bryk 1986).

Results and discussion

The spatiotemporal character of O_3

In view of real-monitoring O_3 concentration data, annual concentration was $55.53 \mu\text{g m}^{-3}$ in China during 2015. A total of 97.39% and 99.19% of stations exceeded the first level of the hourly average concentration ($> 160 \mu\text{g m}^{-3}$) and the 8-h maximum concentration ($> 100 \mu\text{g m}^{-3}$) limitation according to the NAAQS (National Ambient Air Quality Standards) over the whole year, respectively (CSEPA 2012). The time series of monthly O_3 concentrations featured an inverted U-shaped curve, as shown in Fig. 3. In the first half of the year, O_3 concentration gradually increased by 119.30%. The most severe O_3 pollution occurred in May with an average concentration of $73.15 \mu\text{g m}^{-3}$, and 11.95% of monitoring stations had O_3 concentrations higher than $100 \mu\text{g m}^{-3}$. During the period from August to December, O_3 concentration represented a decline trend overall, but there was a slight increase in October, and the lowest average O_3 concentration of $29.52 \mu\text{g m}^{-3}$ emerged in December. The increase in O_3 concentration was possibly related to the O_3 episodes in South China during autumn, which were influenced by the interaction among East Asian monsoon, tropical cyclones and land–sea breeze (Chan and Chan 2000; Fan et al. 2008). In addition, agricultural activities and wheat straw burning in October also contributed to the increase in O_3 concentrations (Fu and Chen 2017; Gong et al. 2017; Macdonald et al. 2011).

The spatial distribution of seasonal O_3 concentration is shown in Fig. 4. During spring, the northern area of China suffered from high O_3 concentrations. The seasonal average concentration of O_3 was higher than $85 \mu\text{g m}^{-3}$ at approximately 11.46% of stations. In summer, O_3 -contaminated areas further expanded. The most polluted areas covered North China, northern East China and some regions of Northwest China. Approximately 23.97% of monitoring stations had concentrations that exceeded $85 \mu\text{g m}^{-3}$ concentration. The concentration significantly decreased in autumn and winter. However, the O_3 levels in YRD and Pearl River Delta (PRD) were relatively higher than those in other areas, and the average concentrations in YRD and PRD were approximately $62.79 \mu\text{g m}^{-3}$ and $58.43 \mu\text{g m}^{-3}$ in autumn, respectively. In PRD, the relative dry and less windy

Fig. 3 The time series of monthly O₃ concentrations

atmospheric condition caused the increase in O₃ concentrations during autumn (Li et al. 2014). In YRD, the anthropogenic heat emissions changed the local meteorological conditions to some extent, which kept photochemical reactions highly active during autumn (Li et al. 2019b).

The random and fixed effects behind O₃ episodes

In this study, multilevel regression models with three levels were constructed to reveal the dominating driving forces behind O₃ episodes varying in time and region. In the multilevel regression models, the variances of intercept and slope among groups conveyed the spatiotemporal heterogeneity of tropospheric O₃ concentration and driving factor effects (Tables 2, 3 and Figs. 5, 6 and Figs. S1–S3) across China. These groups were divided by the season and station codes at each level in multilevel regression model. Moreover, the coefficient reflected the relative influences of the driving forces on O₃ pollution among groups.

The outcomes of the multilevel regression models are listed in Tables 2 and 3. The results indicated that 29.07% of the variance in O₃ concentrations originated from spatiotemporal heterogeneity, which explained approximately 49.5% of O₃ concentration variation. When ICC is larger than 5.9%, the

autocorrelation of O₃ concentration cannot be ignored (Muller 1989). As a consequence, it is necessary to explore the determinants of O₃ variation at different scales separately. While incorporating explanatory variables, the multilevel regression models could explain as much as approximately 98.2% of the variance in the O₃ concentration, and the explained variance at the monthly and seasonal levels increases by 49.39% and 98.99%, respectively. The socioeconomic indicators in Model 3 could decrease the variance by 38.74% and 36.45% at the third level compared with that in Model 1 and Model 2, respectively.

Fixed effects uncovered the average influences of the independent variables on O₃ concentration. All the coefficients, except that of LPGC, were statistically significant at 1% confidence level. In Model 3, LPGC significantly impacted O₃ pollution at 5% confidence level. For monthly explanatory variables, T, PBLH and MW had positive correlations with O₃ pollution. RH, TP, ZW and AP affected O₃ concentration negatively. Additionally, the concentrations of both PM_{2.5} and NO₂ in the air had negative relationships with O₃ concentration. VC was associated with O₃ pollution inversely in Model 2, but showed positive correlation in Model 3. Model 3 explained more variance at the third level than that of Model 2. Therefore, we regarded that the performance of Model 3 was

Fig. 4 The seasonal distribution of monitored O₃ concentrations (a–d reflect the O₃ concentration in spring, summer, autumn and winter, respectively)

improved compared with Model 2, and the result of Model 2 bias reflected the influence of vegetation coverage. Vegetation coverage should have a positive influence on O₃ level. For anthropogenic influences, PD, CPRA, GIO and EIS exhibited consistent trends with O₃ concentration. BN, PGRP, TGRP, GC, LPGC and ESO₂ exerted negative effects on O₃ pollution. Among all the explanatory variables, atmospheric pressure exhibited maximum negative effects on O₃

pollution, while GIO showed maximum positive relationship with O₃ concentration.

The spatiotemporal distribution of tropospheric O₃ pollution determinants

The influences of meteorological factors on O₃ concentration refer to simultaneous physical and chemical processes. The main influences on O₃

Table 2 The outcomes of multilevel regression models (Null Model, Model 1 and Model 2)

Variance	Null model	Model 1	Model 2	Variables	Null model	Model 1	Model 2
<i>Random effects</i>				<i>Fixed effects</i>			
Variance ($I_{\text{season/station}}$)	0.141***	3.533***	3.405***	Intercept	3.816***	19.230***	19.490***
Variance (I_{season})	0.099***	0.006***	0.002***	RH		− 1.737***	− 1.732***
Variance (I_{month})	0.245***	0.124***	0.124***	T		0.180***	0.186***
<i>Model performance</i>				PBLH		0.594***	0.594***
ICC (season/station)	29.07%			TP		− 0.458***	− 0.463***
ICC (season)	20.41%			ZW		− 0.741***	− 0.742***
ICC (month)	50.52%			MW		0.172***	0.169***
EVP ^a		49.39%	98.99%	SP		− 16.690***	− 16.70***
R^2	0.495	0.982	0.982	PM _{2.5}		− 1.162***	− 1.157***
				NO ₂		− 1.962***	− 1.961***
				VC			− 6.998***

*10% statistical significance **5% statistical significance ***1% statistical significance. ICC (intergroup correlation coefficient) = $\sigma_i^2 / \sum_{i=1}^3 \sigma_i^2$, where subscript i represents the i th level

^aEVP (explained variance proportion) = $(v_{ij} - v_{0j}) / v_{0j} \times 100\%$, where v_{0j} represents the variance of j th layer in the null model. v_{ij} is the variance of the j th layer in the i th model

Table 3 The outcomes of multilevel regression model (Model 3)

<i>Random effects</i>					
Variance ($I_{\text{season/station}}$)	2.164***	Variance (I_{season})	0.012***	Variance (I_{month})	0.123***
<i>Fixed effects</i>					
Variables	Coefficient	Variables	Coefficient	Variables	Coefficient
Intercept	20.320***	SP	− 17.220***	PGRP	− 1.127***
RH	− 1.697***	PM _{2.5}	− 1.220***	TGRP	− 2.323***
T	0.173***	NO ₂	− 1.867***	GC	− 2.040***
PBLH	0.635***	VC	2.105***	LPGC	− 0.599**
TP	− 0.511***	PD	4.004***	GIO	4.767***
ZW	− 0.777***	BN	− 2.789***	ESO2	− 4.483***
MW	0.172***	CPRA	2.100***	EIS	2.927***

concentration are attributed to dominant process. Thus, the impacts of meteorological indicators on O₃ concentration show significant spatiotemporal heterogeneity (Fig. S2). Moreover, the O₃ formation closely related to NO_x concentration. The strong oxidation capacity of O₃ leads to complex chemistry reaction with other air pollutants and further deteriorates air quality. As a consequence, we also investigated the relationship among NO₂, PM_{2.5} and O₃ concentration (Fig. S3). In summary, negative relationships between NO₂ and O₃ concentration were found in the most regions of China over the whole year. However, the

concentration of NO₂ in northern Northeast China and Anhui Province, correlated with O₃ pollution positively during spring and autumn. O₃ affects PM_{2.5} formation positively under high O₃ level condition. Conversely, the decrease in PM_{2.5} results in O₃ concentration climbing under high PM_{2.5} level condition.

Figure 5 shows the spatiotemporal distribution of vegetation coverage influences on O₃ pollution. Overall, vegetation coverage had positive impacts on the concentration of O₃. BVOCs emitted from vegetation are one of the important photochemistry

Fig. 5 The spatial distributions of vegetation coverage influences on O₃ concentration

Fig. 6 Spatial distributions of socioeconomic factors influences on O₃ concentrations

precursors. Therefore, vegetation coverage represents a positive impact on the concentration of O₃ (Bai et al. 2017). Furthermore, the impacts of vegetation coverage contributed to the spatial heterogeneity, with negligible seasonal variance at national level. Vegetation positive influence was more prominent in Northwest China and some regions in Southwest China. Since the strong solar radiation in western

China is the breeding ground for the conversion of BVOCs to O₃, BVOCs are also more reactive than anthropogenic VOCs (Li et al. 2019c; Wei et al. 2007). Furthermore, Yli-Pelkonen et al. (2017) found that urban vegetation contributed less to the decrease in the O₃ concentration. One of the reasons is that thick canopies can reduce air flow and obstruct pollutant diffusion, which results in O₃ accumulation.

The spatial pattern differences of socioeconomic influences were also more significant than those of seasons. Overall, the correlation of the most socioeconomic indicators and O_3 concentration was positive in Northwest China and Southwest China (Fig. 6). The transport and industrial emissions, economic development and energy consumption positively affected the concentration of tropospheric O_3 in western China. In early twenty-first century, “Energy Golden Triangle” and the largest coal-to-liquids industry were constructed in Northwest China under national strategies of “Grand Western Development” and “West–East energy transmission programmes” (Liang et al. 2019). These heavy industries caused a large amount of pollutants emissions. Besides, they contributed much to the economy development in Northwest China. Therefore, economy increase impacts O_3 pollution positively in western China. Conversely, the O_3 concentration in Northeast China, North China and some stations in Central China, Shanghai City and the coastal South China had strong and negative correlations with TGRP, since the adoption of new technologies and increased investment in environmental governance were beneficial for improving the atmospheric environment with continuous economic development, especially in Northeast China and North China where the secondary industry was dominant (Liu et al. 2019a). Moreover, the cities with better economic development have more investment in pollution control (Zhao et al. 2019). For energy consumption impacts, GC and LPGC represented negative impacts on O_3 concentration in Central China and Northeast China. However, the influences were opposite in about 15.77% and 24.69% of stations mainly distributing in Fujian and Guangdong provinces. The hydrocarbon (HC) species originating from liquefied petroleum (LPG) combustion are in favor of O_3 formation (Blake and Rowland 1995). As a consequence, the usage of LPG exerts positive correlation with tropospheric O_3 . Conversely, because of the advantage of less air pollutant emissions, gas and LPG are regarded as environment friendly fuel in Central China and Northeast China where fossil fuels are the dominant source of energy (Liu et al. 2019b; NBSC 2016b). It is exhibited that LPG and gas consumption are related to O_3 concentration inversely in these regions. The BN influences displayed significantly different characteristics. Developed public transport was conducive to mitigating the O_3 pollution in some regions of Central China and coastal area of South China.

Conversely, the positive influences of BN were observed in Northwest China, some regions of North China and Southwest China. On the one hand, the usage of buses can reduce the emissions of taxis and private cars to some extent. Moreover, some buses have used new energy in China in recent years. This kind of public transport is more environmentally friendly than conventional diesel buses (Zhang et al. 2014). In contrast, public transport contributes less to the decrease in private car and taxi emissions in sparsely populated cities in Northwest China, North China and Southwest China. The emissions from buses also exert positive impacts on air pollution.

Limitations and future work

There are also a few of limitations in this research. First, the multilevel model only explains correlation between tropospheric O_3 and driving forces. The causal relationship cannot be revealed by regression model. Consequently, the statistical method, such as Granger test, will be integrated into the multilevel model in our future work. Moreover, there are always nonlinear relationship between O_3 concentration and driving forces. However, the multilevel linear model is competent for reflecting linear relationship. Besides Granger test, nonlinear statistical method will be also combined with multilevel model in our future research. On the other hand, we only focus on the determinants of O_3 concentration at monitoring station in this research dispersedly. The remote effects resulting from atmosphere transport are always ignored by statistical model. Thus, the temporally and spatially heterogeneous response of O_3 pollution to anthropogenic activities and meteorology changes will be explored based on space–time continuous tropospheric O_3 concentration data in the future.

Policy implications

As previous scientific publications, controlling the O_3 precursors emitted from industrial production, solvent usage, vehicle exhaust, energy usage and vegetation emissions contributes much to O_3 reductions (Shao et al. 2016). Meanwhile, meteorology conditions also exhibit important impacts on tropospheric O_3 formation. Consequently, we took the spatiotemporal heterogeneity of biophysical and socioeconomic influences into consideration to highlight the regions where

atmospheric environment was easily contaminated by O_3 . The rule depicted that the regions would be marked as two-level potential O_3 -contaminated areas. The Level I potential O_3 -contaminated areas were characterized as covering the suitable atmospheric environment where at least three meteorological

factors play positive roles in O_3 formation simultaneously. Level II-contaminated areas were under high risk of being O_3 -contaminated which were influenced by at least three positive meteorological and five socioeconomic factors simultaneously (Fig. 7). The results indicated that the atmospheric environment in

Fig. 7 The potentially O_3 -contaminated areas (at least three meteorological factors had positive impacts in the Level I area. At least three meteorological and five socioeconomic factors

exerted positive influences in the Level II area. Besides, **a–d** reflect the conditions in spring, summer, autumn and winter, respectively)

East China and South China was always suitable for O_3 formation over the whole year. Temperature, PBLH and zonal wind were the major factors influencing O_3 concentration positively and should be regarded as key observations. Moreover, the meteorological conditions in Central China during spring, autumn and winter and the atmospheric environment in Northeast China during spring, summer and winter were advantageous for O_3 formation and accumulation. In these regions, both the local emission and O_3 precursors transmission should be closely focused. The tropospheric O_3 episodes emerging in Northwest China and Southwest China were much influenced by socioeconomic activities over the whole year. During spring and summer, transport and industrial emissions in South China also worked as positive anthropogenic indicators. Moreover, the concentrations of NO_2 and $PM_{2.5}$ should be closely considered. LPG and bus usage are necessary to be controlled in the cities of South China during summer as well. As has been stated, these proposed measures comprise a powerful method for mitigating O_3 pollution in each region and season.

Conclusion

Tropospheric O_3 concentration was characterized by significant spatiotemporal heterogeneity with serious O_3 episodes over Southwest China, Northwest China, North China and northern East China from spring to autumn. This phenomenon results from the pronounced spatial and temporal heterogeneity of the driving forces at different levels. However, previous research using statistical methods seldom considers multi-scale effects of biophysical and socioeconomic influences on O_3 level. In this study, we employed a three-level regression model to investigate the dominant driving forces in each region varying seasons. The monthly, seasonal and regional variations in O_3 concentration were explained by meteorological, vegetation and socioeconomic factors at three levels in the multilevel regression models, respectively.

Meteorological factors including temperature, planet layer boundary layer height and zonal wind had more significant impacts on O_3 concentration in coastal regions including South China and East China than that in other regions. In inland areas that are characterized as ecologically fragile including

Northwest China and western North China, anthropogenic sources significantly played positive roles in O_3 concentration. The determinants of tropospheric O_3 episodes exhibited significant seasonal heterogeneity in the cities which were located in the middle transition zone between the two regions mentioned above. In summary, the tropospheric O_3 concentration covering the regions near coastal area is strongly influenced by meteorology condition. In contrast, tropospheric O_3 level over inland regions mainly depends on the emission intensity from anthropogenic sources.

Acknowledgements This work was financially supported by the National Key R&D Program of China (Grant Number: 2018YFB0505402) and the National Natural Science Foundation of China (Grant Number: 41871301 and 41771429). Special thanks are due to Mr. Henok Girmatsion for the help in language editing.

References

- Bai, J., Guenther, A., Turnipseed, A., Duhl, T., & Greenberg, J. (2017). Seasonal and interannual variations in whole-ecosystem BVOC emissions from a subtropical plantation in China. *Atmospheric Environment*, 161, 176–190. <https://doi.org/10.1016/j.atmosenv.2017.05.002>.
- Blake, D. R., & Rowland, F. S. (1995). Urban leakage of liquefied petroleum gas and its impact on Mexico-City Air-Quality. *Science*, 269(5226), 953–956. <https://doi.org/10.1126/science.269.5226.953>.
- Calvin, J. A. (1994). Hierarchical linear models: Applications and data analysis methods. *Technometrics*, 36(1), 116–117. <https://doi.org/10.1080/00401706.1994.10485413>.
- Chan, C. Y., & Chan, L. Y. (2000). Effect of meteorology and air pollutant transport on ozone episodes at a subtropical coastal Asian city. *Hong Kong. Journal of Geophysical Research-Atmospheres*, 105(D16), 20707–20724. <https://doi.org/10.1029/2000jd900140>.
- Chen, X., Situ, S., Zhang, Q., Wang, X., Sha, C., Zhou, L., et al. (2019). The synergetic control of NO_2 and O_3 concentrations in a manufacturing city of southern China. *Atmospheric Environment*, 201, 402–416. <https://doi.org/10.1016/j.atmosenv.2018.12.021>.
- Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., et al. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, 389(10082), 1907–1918. [https://doi.org/10.1016/S0140-6736\(17\)30505-6](https://doi.org/10.1016/S0140-6736(17)30505-6).
- CSEPA, S. E. P. A. (2012). Ambient air quality standards (on trial) national environmental protection standards of the People's Republic of China. In (Vol. GB3095-2012). Beijing: State Environmental Protection Agency.
- Fan, S. J., Wang, B. M., Tesche, M., Engelmann, R., Althausen, A., Liu, J., et al. (2008). Meteorological conditions and

- structures of atmospheric boundary layer in October 2004 over Pearl River Delta area. *Atmospheric Environment*, 42(25), 6174–6186. <https://doi.org/10.1016/j.atmosenv.2008.01.067>.
- Fang, C., Liu, H., Luo, K., & Xiaohua, Y. U. (2017). Comprehensive regionalization of human geography in China. *Acta Geographica Sinica*, 72(2), 179–196.
- Fu, H., & Chen, J. (2017). Formation, features and controlling strategies of severe haze-fog pollutions in China. *Science of the Total Environment*, 578, 121–138. <https://doi.org/10.1016/j.scitotenv.2016.10.201>.
- GMAO. (2015a). *MERRA-2 instU_2d_asm_Nx: 2d, diurnal, instantaneous, single-level, assimilation, single-level diagnostics V5.12.4*. Greenbelt, MD: Goddard Earth Sciences Data and Information Services Center (GES DISC).
- GMAO. (2015b). *MERRA-2 tavgU_2d_flg_Nx: 2d, diurnal, time-averaged, single-level, assimilation, surface flux diagnostics V5.12.4*. Greenbelt, MD: Goddard Earth Sciences Data and Information Services Center (GES DISC).
- GMAO. (2015c). *MERRA-2 tavgU_2d_lnd_Nx: 2d, diurnal, time-averaged, single-level, assimilation, land surface diagnostics V5.12.4*. Greenbelt, MD: Goddard Earth Sciences Data and Information Services Center (GES DISC).
- Gong, X., Hong, S., & Jaffe, D. A. (2018). Ozone in China: Spatial distribution and leading meteorological factors controlling O₃ in 16 Chinese Cities. *Aerosol and Air Quality Research*, 18(9), 2287–2300. <https://doi.org/10.4209/aaqr.2017.10.0368>.
- Gong, X., Kaulfus, A., Nair, U., & Jaffe, D. A. (2017). Quantifying O₃ impacts in urban areas due to wildfires Using a generalized additive model. *Environmental Science and Technology*, 51(22), 13216–13223. <https://doi.org/10.1021/acs.est.7b03130>.
- Hao, Y., & Liu, Y.-M. (2016). The influential factors of urban PM_{2.5} concentrations in China: A spatial econometric analysis. *Journal of Cleaner Production*, 112, 1443–1453. <https://doi.org/10.1016/j.jclepro.2015.05.005>.
- Hu, J., Li, Y., Zhao, T., Liu, J., Hu, X.-M., Liu, D., et al. (2018). An important mechanism of regional O₃ transport for summer smog over the Yangtze River Delta in eastern China. *Atmospheric Chemistry and Physics*, 18(22), 16239–16251. <https://doi.org/10.5194/acp-18-16239-2018>.
- Huang, J. P., Zhou, C. H., Lee, X. H., Bao, Y. X., Zhao, X. Y., Fung, J., et al. (2013). The effects of rapid urbanization on the levels in tropospheric nitrogen dioxide and ozone over East China. *Atmospheric Environment*, 77, 558–567. <https://doi.org/10.1016/j.atmosenv.2013.05.030>.
- Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, 525(7569), 367–371. <https://doi.org/10.1038/nature15371>.
- Li, J., Liu, Q. H., Zhao, J., Mu, X., Lin, S., Zhong, B., et al. (2017). *The vegetation coverage data set with 1 km/5d resolution of the Belt and Road and its adjacent area (2015)*. Retrieved Global Change and Research Data Publishing & Repository from <http://geodoi.ac.cn/WebCn/Default.aspx>.
- Li, J., Lu, K., Lv, W., Li, J., Zhong, L., Ou, Y., et al. (2014). Fast increasing of surface ozone concentrations in Pearl River Delta characterized by a regional air quality monitoring network during 2006–2011. *Journal of Environmental Sciences*, 26(1), 23–36. [https://doi.org/10.1016/s1001-0742\(13\)60377-0](https://doi.org/10.1016/s1001-0742(13)60377-0).
- Li, K., Jacob, D. J., Liao, H., Shen, L., Zhang, Q., & Bates, K. H. (2019a). Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China. *Proceedings of the National Academy of Sciences of the United States of America*, 116(2), 422–427. <https://doi.org/10.1073/pnas.1812168116>.
- Li, L., An, J., Huang, L., Yan, R., Huang, C., & Yarwood, G. (2019b). Ozone source apportionment over the Yangtze River Delta region, China: Investigation of regional transport, sectoral contributions and seasonal differences. *Atmospheric Environment*, 202, 269–280. <https://doi.org/10.1016/j.atmosenv.2019.01.028>.
- Li, R., Wang, Z., Cui, L., Fu, H., Zhang, L., Kong, L., et al. (2019c). Air pollution characteristics in China during 2015–2016: Spatiotemporal variations and key meteorological factors. *Science of the Total Environment*, 648, 902–915. <https://doi.org/10.1016/j.scitotenv.2018.08.181>.
- Liang, X., Huang, T., Lin, S., Wang, J., Mo, J., Gao, H., et al. (2019). Chemical composition and source apportionment of PM₁ and PM_{2.5} in a national coal chemical industrial base of the Golden Energy Triangle, Northwest China. *Science of the Total Environment*, 659, 188–199. <https://doi.org/10.1016/j.scitotenv.2018.12.335>.
- Liu, H., Fang, C., Zhang, X., Wang, Z., Bao, C., & Li, F. (2017). The effect of natural and anthropogenic factors on haze pollution in Chinese cities: A spatial econometrics approach. *Journal of Cleaner Production*, 165, 323–333. <https://doi.org/10.1016/j.jclepro.2017.07.127>.
- Liu, H., Tian, H., Hao, Y., Liu, S., Liu, X., Zhu, C., et al. (2019a). Atmospheric emission inventory of multiple pollutants from civil aviation in China: Temporal trend, spatial distribution characteristics and emission features analysis. *Science of the Total Environment*, 648, 871–879. <https://doi.org/10.1016/j.scitotenv.2018.07.407>.
- Liu, J., Kiesewetter, G., Klimont, Z., Cofala, J., Heyes, C., Schopp, W., et al. (2019b). Mitigation pathways of air pollution from residential emissions in the Beijing–Tianjin–Hebei region in China. *Environment International*, 125, 236–244. <https://doi.org/10.1016/j.envint.2018.09.059>.
- Macdonald, A. M., Anlauf, K. G., Leaitch, W. R., Chan, E., & Tarasick, D. W. (2011). Interannual variability of ozone and carbon monoxide at the Whistler high elevation site: 2002–2006. *Atmospheric Chemistry and Physics*, 11(22), 11431–11446. <https://doi.org/10.5194/acp-11-11431-2011>.
- Muller, K. (1989). Statistical power analysis for the behavioral sciences. *Technometrics*, 31(4), 499–500. <https://doi.org/10.1080/00401706.1989.10488618>.
- NBSC. (2016a). *China city statistical yearbook*. Beijing: NBSC.
- NBSC. (2016b). *China energy statistical yearbook*. Beijing: NBSC.
- Raudenbush, S., & Bryk, A. S. (1986). A hierarchical model for studying school effects. *Sociology of Education*, 59(1), 1–17. <https://doi.org/10.2307/2112482>.
- Shao, P., An, J. L., Xin, J. Y., Wu, F. K., Wang, J. X., Ji, D. S., et al. (2016). Source apportionment of VOCs and the contribution to photochemical ozone formation during

- summer in the typical industrial area in the Yangtze River Delta, China. *Atmospheric Research*, 176, 64–74. <https://doi.org/10.1016/j.atmosres.2016.02.015>.
- Si, Y., Li, S., Chen, L., Yu, C., Wang, Z., Wang, Y., et al. (2018). Validation and spatiotemporal distribution of GEOS-5-based planetary boundary layer height and relative humidity in China. *Advances in Atmospheric Sciences*, 35(4), 479–492. <https://doi.org/10.1007/s00376-017-6275-3>.
- Sun, L., Xue, L., Wang, Y., Li, L., Lin, J., Ni, R., et al. (2019). Impacts of meteorology and emissions on summertime surface ozone increases over central eastern China between 2003 and 2015. *Atmospheric Chemistry and Physics*, 19(3), 1455–1469. <https://doi.org/10.5194/acp-19-1455-2019>.
- Tai, A. P. K., Martin, M. V., & Heald, C. L. (2014). Threat to future global food security from climate change and ozone air pollution. *Nature Climate Change*, 4(9), 817–821.
- Wang, T., Xue, L. K., Brimblecombe, P., Lam, Y. F., Li, L., & Zhang, L. (2017). Ozone pollution in China: A review of concentrations, meteorological influences, chemical precursors, and effects. *Science of the Total Environment*, 575, 1582–1596. <https://doi.org/10.1016/j.scitotenv.2016.10.081>.
- Wei, X. L., Li, Y. S., Lam, K. S., Wang, A. Y., & Wang, T. J. (2007). Impact of biogenic VOC emissions on a tropical cyclone-related ozone episode in the Pearl River Delta region. *China Atmospheric Environment*, 41(36), 7851–7864. <https://doi.org/10.1016/j.atmosenv.2007.06.012>.
- Yang, J., Chang, Y., & Yan, P. (2015). Ranking the suitability of common urban tree species for controlling PM 2.5 pollution. *Atmospheric Pollution Research*, 6(2), 267–277. <https://doi.org/10.5094/apr.2015.031>.
- Yang, Y. C., Liu, X. G., Zheng, J., Tan, Q. W., Feng, M., Qu, Y., et al. (2019). Characteristics of 1-year observation of VOCs, NO_x, and O₃ at an urban site in Wuhan, China. *Journal of Environmental Sciences-China*, 79, 297–310. <https://doi.org/10.1016/j.jes.2018.12.002>.
- Yli-Pelkonen, V., Setälä, H., & Viippola, V. (2017). Urban forests near roads do not reduce gaseous air pollutant concentrations but have an impact on particles levels. *Landscape and Urban Planning*, 158, 39–47. <https://doi.org/10.1016/j.landurbplan.2016.09.014>.
- Zhan, D., Kwan, M.-P., Zhang, W., Yu, X., Meng, B., & Liu, Q. (2018). The driving factors of air quality index in China. *Journal of Cleaner Production*, 197, 1342–1351. <https://doi.org/10.1016/j.jclepro.2018.06.108>.
- Zhang, G., Xu, H. H., Qi, B., Du, R. G., Gui, K., Wang, H. L., et al. (2018). Characterization of atmospheric trace gases and particulate matter in Hangzhou, China. *Atmospheric Chemistry and Physics*, 18(3), 1705–1728. <https://doi.org/10.5194/acp-18-1705-2018>.
- Zhang, S., Wu, Y., Liu, H., Huang, R., Yang, L., Li, Z., et al. (2014). Real-world fuel consumption and CO₂ emissions of urban public buses in Beijing. *Applied Energy*, 113, 1645–1655. <https://doi.org/10.1016/j.apenergy.2013.09.017>.
- Zhao, X., Zhou, W., Han, L., & Locke, D. (2019). Spatiotemporal variation in PM_{2.5} concentrations and their relationship with socioeconomic factors in China's major cities. *Environment International*, 133(Pt A), 105145. <https://doi.org/10.1016/j.envint.2019.105145>.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.