2 Meteorological influence on surface ozone trends in China:

3 Assessing uncertainties caused by multi-dataset and

- 4 multi-method
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15 Abbreviations¹

¹ Abbreviations:

CMA: China Meteorological Administration

ECMWF: European Centre for Medium-Range Weather Forecasts

ERA5: The fifth generation ECMWF atmospheric reanalysis of the global climate

ERA-Interim: ECMWF Reanalysis - Interim

FNL: National Centers for Environmental Prediction Final Operational Global Analysis data (1.0°×1.0°)

FNL025: National Centers for Environmental Prediction Final Operational Global Analysis data (0.25°×0.25°)

MERRA2: Modern-Era Retrospective analysis for Research and Applications Version 2

KZ: Kolmogorov–Zurbenko filter

MLR: Multiple Linear Regression

RF: Random Forest

XGBoost: eXtreme Gradient Boosting

LightGBM: Light Gradient Boosting Machine Lowess: Locally Weighted Linear Regression GEOS: Goddard Earth Observing System WRF: Weather Research and Forecast CMAQ: Community Multiscale Air Quality

WRF-Chem: WRF model coupled with Chemistry

RegCM-Chem-YIBs: Regional Climate-Chemistry-Ecology Coupling Model

NCP: North China Plain

BTH: Beijing-Tianjin-Hebei Region YRD: Yangtze River Delta Region

PRD: Pearl River Delta SCB: Sichuan Basin FWP: Fenwei Plain THB: Twain-Hu Basin

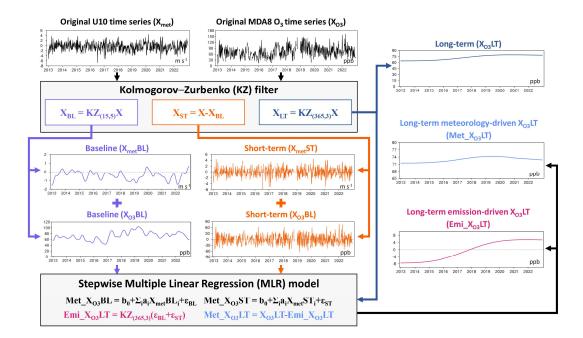


Figure S1. Flowchart of temporal decomposition of observed MDA8 O₃ time series into meteorology-driven and emission-driven long-term components (an example of the MDA8 O₃ data from Station 1015A and U10 data from ERA5).

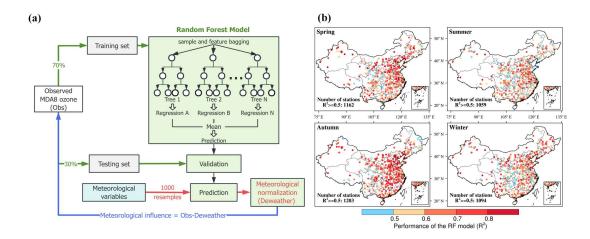


Figure S2. (a) Conceptual diagram of obtaining the meteorological influence based on the Random Forest (RF) algorithm, and (b) the performance of the RF model for the testing dataset at each state-controlled station during four seasons. The number of state-controlled monitoring stations with the coefficient of determination (\mathbb{R}^2) greater than or equal to 0.5 is also presented.

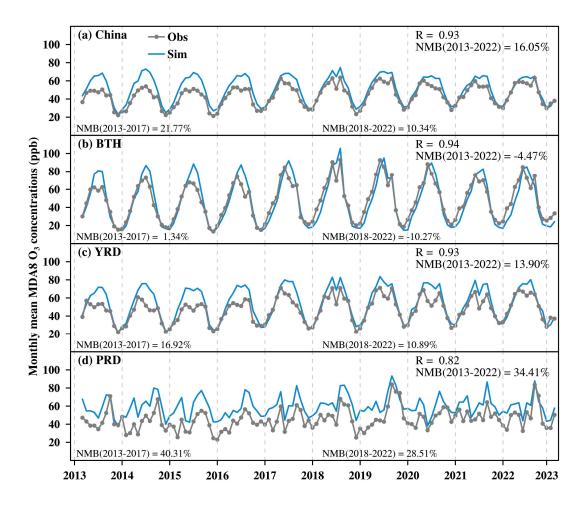


Figure S3. Comparison of simulated (blue) and observed (grey) monthly mean MDA8 O₃ concentrations averaged over (a) China, (b) BTH, (c) YRD, and (d) PRD from 2013 to 2022. The correlation coefficient (R) and normalized mean bias (NMB) values are shown. The NMB for 2013–2017 and 2018–2022 are also calculated and shown in order to test the performance of GEOS-Chem at different time periods.

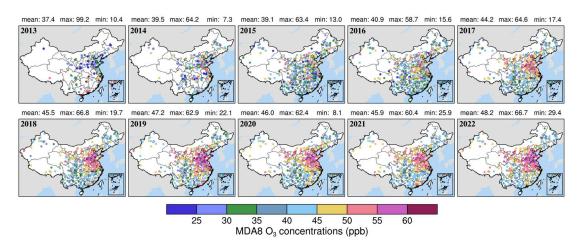


Figure S4. Annual mean MDA8 O₃ concentrations in China from 2013 to 2022. The mean, maximum, and minimum MDA8 O₃ concentrations for the whole China are shown.

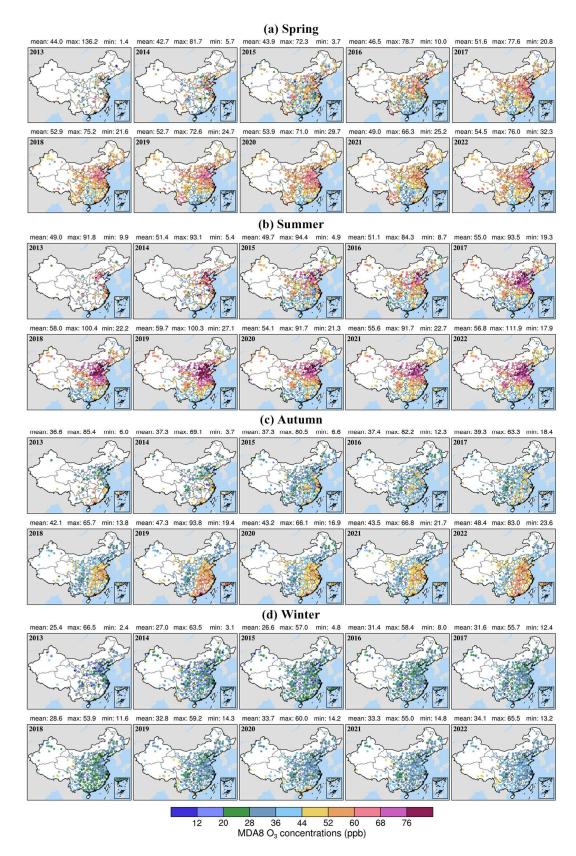


Figure S5. Seasonal mean MDA8 O₃ concentrations in China during (a) spring, (b) summer, (c) autumn, and (d) winter. The mean, maximum, and minimum MDA8 O₃ concentrations for the whole China are shown.

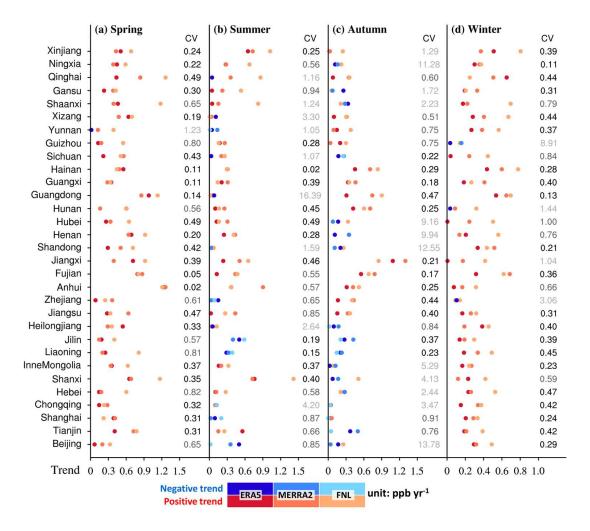


Figure S6. Trends in meteorology-driven MDA8 O₃ concentrations calculated by ERA5-, MERRA2-, and FNL-driven MLR models in China's 31 mainland provinces during (a) spring, (b) summer, (c) autumn, and (d) winter. Markers in red and blue represent the positive and negative trends, respectively. The absolute value of coefficient of variation (CV) are shown. The CV is calculated by the standard deviation of trends derived from ERA5-, MERRA2-, and FNL-driven MLR models divided by the mean. The darker colour means the lower uncertainty in quantifying the meteorological impact on observed O₃ trends.

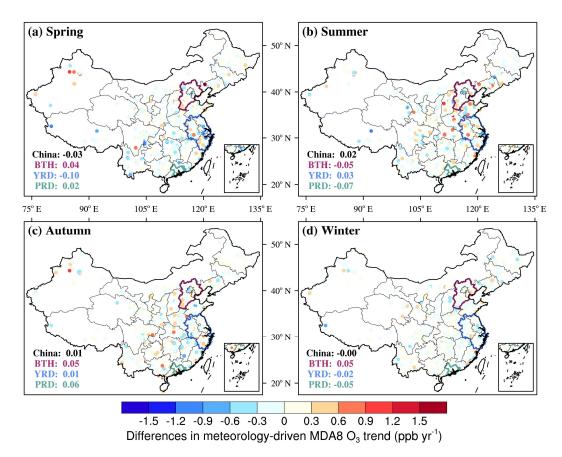


Figure S7. Differences between meteorology-driven MDA8 O₃ trends calculated by FNL- and FNL025-driven MLR model in China during (a) spring, (b) summer, (c) autumn, and (d) winter. Values in black, purple, blue, and green represent the average difference for the whole China, BTH, YRD, and PRD, respectively.

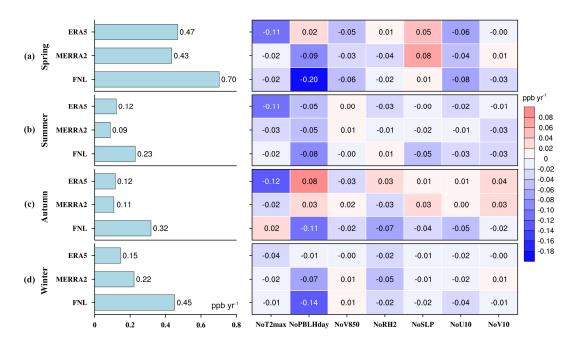


Figure S8. Construction of a multiple linear regression (MLR) model using seven common meteorological variables (i.e. T2max, PBLHday, V850, RH2, SLP, U10, V10) from ERA5, MERRA2, and FNL to quantify the meteorological influence on the MDA8 O₃ trends during (a) spring, (b) summer, (c) autumn, and (d) winter. Bars on the left represent the meteorology-driven O₃ trends derived from the three data-driven MLR models. The heatmap on the right represents the difference between the results obtained by constructing an MLR model after removing a certain meteorological variable in sequence.

Meteorology-driven MDA8 O₃ trend from MLR and GC

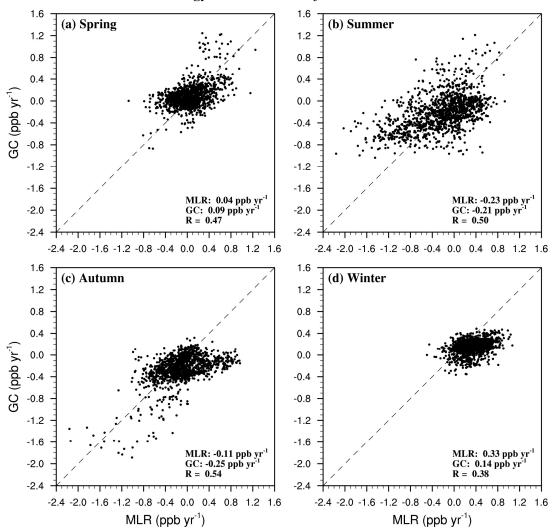


Figure S9. The comparison of meteorology-driven O₃ trends from the MERRA2-driven multiple linear regression (MLR) vs. GEOS-Chem (GC) model averaged over China for 2018–2022 during (a) spring, (b) summer, (c) autumn, and (d) winter. The dashed line is a 1:1 line. Coefficient of correlation (R) is also shown.

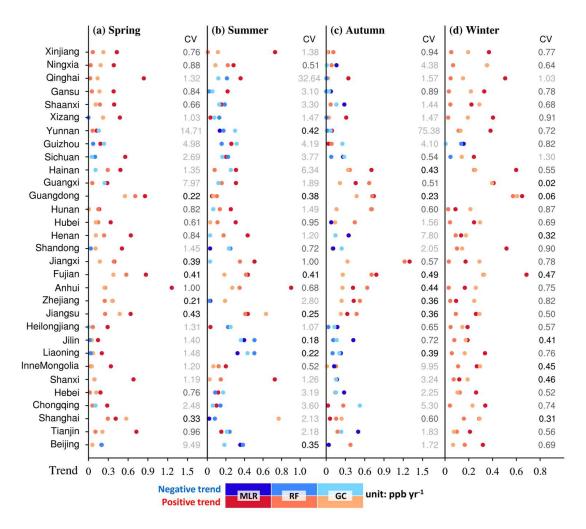


Figure S10. Trends in meteorology-driven MDA8 O₃ concentrations calculated by multiple linear regression (MLR), random forest (RF), and GEOS-Chem (GC) models in China's 31 mainland provinces during (a) spring, (b) summer, (c) autumn, and (d) winter. Markers in red and blue represent the positive and negative trends, respectively. The CV is calculated by the standard deviation of the trends derived from MLR, RF, and GC models divided by the mean. The darker colour means the lower uncertainty in quantifying the meteorological impact on observed O₃ trends.

7 Table S1. Reported studies using traditional statistical, machine learning, and chemical transport models to obtain the meteorological impact on surface O₃ in the past six years.

Region/City	Study period ^a	Model	Meteorological data	Meteorological impact ^b	Reference	
Shanghai	2013–2017	KZ	N/A	+0.75 μg m ⁻³ yr ⁻¹	Yu et al., 2019	
	Spring, 2009–2015			−1.11 ppb yr ^{−1}		
TT:	Summer, 2009–2015		C' 1	+0.12 ppb yr ⁻¹	W . 1 2010	
Tianjin	Autumn, 2009–2015	Generalized additive model	Site observation	$-0.99~\mathrm{ppb~yr^{-1}}$	Yang et al., 2019a	
	Winter, 2009-2015			$\pm 0.06~\mathrm{ppb~yr^{-1}}$		
PRD	2007–2017	KZ-MLR	ECMWF reanalysis	–0.8 μg m ^{–3} yr ^{–1}	Yang et al., 2019b	
North China				+0.2±1.1 ppb		
Northeast China	A G 2012/2017	WDE CMAO	27/4	+0.3±0.8 ppb	D' 1 2010	
East China	Apr to Sept, 2013/2017	WRF-CMAQ	N/A	+2.0±1.7 ppb	Ding et al., 2019	
South China				+0.5±1.5 ppb		
China				-3.2 ppb		
North China				−8.7 ppb		
Northeast China				-4.5 ppb		
East China	Summer, 2013/2014			−1.1 ppb		
South central China				−1.5 ppb		
Southwest China				−3.7 ppb		
Northwest China		WDF CMAO		−1.6 ppb	W . 1 2010	
China		- WRF-CMAQ	FNL	−1.8 ppb	— Wang et al., 2019	
North China				−2.4 ppb		
Northeast China				−0.5 ppb		
East China	Summer, 2013/2015			-2.1 ppb		
South central China				-4.2 ppb		
Southwest China				+0.2 ppb		
Northwest China				−0.9 ppb		

Region/City	Study period	Model	Meteorological data	Meteorological impact	Reference	
Central eastern China	2003/2015	GEOS-Chem	MERRA2	+3.2 ppb	Sun et al., 2019	
Eastern China				+0.5 μg m ⁻³ yr ⁻¹		
BTH	G 2012 2019	MID	ENI	$+0.7~\mu g~m^{-3}~yr^{-1}$	11 4 1 2020	
YRD	Summer, 2013–2018	MLR	FNL	$+0.9~\mu g~m^{-3}~yr^{-1}$	Han et al., 2020	
PRD				$+0.7~\mu g~m^{-3}~yr^{-1}$		
Eastern China				+0.7 ppb yr ⁻¹		
NCP				+1.4 ppb yr ⁻¹		
YRD	Summer, 2013–2019	MLR	MERRA2	+0.7 ppb yr ⁻¹	Li et al., 2020	
PRD				+0.8 ppb yr ⁻¹		
SCB				$-0.2~\mathrm{ppb}~\mathrm{yr}^{-1}$		
China	Summer, 2013–2017	G 2012 2017 WINE CHAIO FIN	ENH	Meteorological changes dominated	1. 117 2020	
		WRF-CMAQ	FNL	the changing rates of O ₃ .	Liu and Wang, 2020	
NCP			$+0.7~\mu g~m^{-3}~yr^{-1}$			
YRD	2014–2018			$+0.7~\mu g~m^{-3}~yr^{-1}$		
FWP				$+0.8~\mu g~m^{-3}~yr^{-1}$		
NCP			_	+0.5 μg m ⁻³ yr ⁻¹	_	
YRD	Spring, 2014–2018			$+1.3~\mu g~m^{-3}~yr^{-1}$		
FWP		MD	EDAT.	$+1.1~\mu g~m^{-3}~yr^{-1}$	C1 1 2020	
NCP		MLR	ERA-Interim —	+0.8 μg m ⁻³ yr ⁻¹	— Chen et al., 2020	
YRD	Summer, 2014–2018			$+1.1~\mu g~m^{-3}~yr^{-1}$		
FWP				$\pm 0.8~\mu g~m^{-3}~yr^{-1}$		
NCP			_	+1.0 μg m ⁻³ yr ⁻¹	_	
YRD	Autumn, 2014–2018			$\pm 0.8~\mu g~m^{-3}~yr^{-1}$		
FWP				$+1.1 \ \mu g \ m^{-3} \ yr^{-1}$		

Region/City	Study period	Model	Meteorological data	Meteorological impact	Reference		
NCP	Winter, 2014–2018			$+0.7~\mu g~m^{-3}~yr^{-1}$			
YRD		MLR	ERA-Interim	$-0.5~\mu g~m^{-3}~yr^{-1}$	Chen et al., 2020		
FWP				$\pm 0.1~\mu g~m^{-3}~yr^{-1}$			
NCP	S 2012 2017	CEOS Cham	MEDDA2	+0.28 ppb yr ⁻¹	Dawa et al. 2021		
YRD	Summer, 2012–2017	GEOS-Chem	MERRA2	+1.47 ppb yr ⁻¹	Dang et al., 2021		
BTH				$+1.07~\mu g~m^{-3}~yr^{-1}$			
YRD	2015 2010	ил мі р	EDAS ENI	$+0.99~\mu g~m^{-3}~yr^{-1}$	Mi11111111111		
PRD	2015–2019	KZ-MLR	ERA5, FNL	$\pm 2.52~\mu g~m^{-3}~yr^{-1}$	Mousavinezhad et al., 2021		
SCB				$-1.35~\mu g~m^{-3}~yr^{-1}$			
	Spring, 2013/2015		FNL	+8.6%			
	Spring, 2013/2017	WRF-Chem		+14.5%			
	Spring, 2013/2019			+14.0%			
	Summer, 2013/2015			-7.4%			
	Summer, 2013/2017			-6.5%			
al I	Summer, 2013/2019			-6.2%	71 1 2021		
Shandong	Autumn, 2013/2015			+6.9%	Zhao et al., 2021		
	Autumn, 2013/2017			+11.6%			
	Autumn, 2013/2019			+9.6%			
	Winter, 2013/2015			-1.2%			
	Winter, 2013/2017			-0.2%			
	Winter, 2013/2019			-0.5%			
CCD	M . I 2010/2020	GEOS-Chem	CEOG ED	11.57 ppb	G 1 2021		
SCB	May to Jun, 2019/2020	GEOS-Chem-XGBoost	GEOS-FP	11.15 ppb	Sun et al., 2021		
			FNL	+2.00 μg m ⁻³ yr ⁻¹	Yao et al., 2021		

Region/City	Study period Model		Meteorological data	Meteorological impact	Reference	
Eastern China				−2.9 ppb		
BTH		CEOG CI		−1.4 ppb		
FWP		GEOS-Chem		−3.2 ppb		
YRD	2010/2020		GEOG ED	−3.2 ppb	Tr 1 2021	
Eastern China	- May to Aug, 2019/2020		GEOS-FP -	-2.3 ppb	Yin et al., 2021	
BTH		ana at wan		-2.2 ppb		
FWP		GEOS-Chem-XGBoost		-2.2 ppb		
YRD				−2.7 ppb		
Eastern and central China	Summer, 2013/2020	4-D meteorology-pollution decomposition model	World Meteorological Organization	Meteorology reduced the O ₃ concentrations.	Lin et al., 2021	
YRD	Apr to Sept, 2014–2018	KZ-MLR	Meteorology decreased (increased) O ₃ CMA from 2014 to the middle of 2016 (from the middle of 2016 to 2018)		Gao et al., 2021a	
Eastern China	May, Jul, Sept, Dec, 2013/2017	WRF-Chem FNL		$-8.1 \sim +21.3 \ \mu g \ m^{-3}$	Li et al., 2021	
	May 1 st to Jun 10 th , 2014–2019			+1.8 ppb yr ⁻¹		
NCP	Jun 11th to Jul 15th, 2014–2019	MLR	FNL	+2.4 ppb yr ⁻¹	Gao et al., 2021b	
	Jul 16th to Aug 31st, 2014–2019	•	-	-0.4 ppb yr ⁻¹		
PRD (urban site) PRD (regional site)	2006–2019	MLR	ERA5	$-0.04~ m ppb~yr^{-1}$ $-0.11~ m ppb~yr^{-1}$	Li et al., 2022	
Beijing	2013–2020	MLR	CMA, ERA5	+2.15 μg m ⁻³ yr ⁻¹	Gong et al., 2022	

Region/City	Study period	Model	Meteorological data	Meteorological impact	Reference		
Beijing				+45%			
Shenzhen	2015–2020	KZ-MLR	National Climatic	+20%	Zhang et al., 2022		
Wuhan	2013–2020	KZ-WLK	Data Center	+60%	Znang et al., 202		
Nanjing				+75%			
YRD				$+5.0~\mu g~m^{-3}~yr^{-1}$			
Shanghai				$+1.0~\mu g~m^{-3}~yr^{-1}$			
Nanjing	Summer, 2015–2019	MLR	MERRA2	$+11.3~\mu g~m^{-3}~yr^{-1}$	Qian et al., 2022		
Hangzhou				$+1.9 \ \mu g \ m^{-3} \ yr^{-1}$			
Heifei				$+6.0~\mu g~m^{-3}~yr^{-1}$			
BTH				$+0.74~\mathrm{ppb~yr^{-1}}$			
YRD		RF		+1.35 ppb yr ⁻¹			
PRD				$-0.75~\mathrm{ppb~yr^{-1}}$			
Sichuan				$-0.91 \; \mathrm{ppb} \; \mathrm{yr}^{-1}$			
BTH	_			+0.54 ppb yr ⁻¹			
YRD	2017 2010		TD . •	$+1.38~{ m ppb}~{ m yr}^{-1}$	Weng et al., 2022		
PRD	Summer, 2015–2019	Ridge regression	ERA5	$-1.13~\mathrm{ppb~yr^{-1}}$			
Sichuan				$-0.84~\mathrm{ppb~yr^{-1}}$			
BTH	_			+0.55 ppb yr ⁻¹	_		
YRD) a p		+1.42 ppb yr ⁻¹			
PRD		MLR		$-1.1~\mathrm{ppb~yr^{-1}}$			
Sichuan				-0.86 ppb yr ⁻¹			
aan	Apr to Aug, 2016/2019	WDD 614.6	77.77	$+6.4~\mu g~m^{-3}$	***		
SCB	Jun to Aug, 2019/2020	WRF-CMAQ	FNL	–12.6 μg m ^{–3}	Wu et al., 2022		
Tianjin	2015–2021	Lowess and RF	CMA	+2.1 μg m ⁻³ yr ⁻¹	Ding et al., 2023		

Region/City	Study period	Model	Meteorological data	Meteorological impact	Reference		
BTH				$-0.02 \pm 2.9~\mu g~m^{-3}$			
FWP				$+7.23 \pm 5.97 \ \mu g \ m^{-3}$			
THB	Summer,	D.F.	ED A 5	$+3.63 \pm 4.51 \ \mu g \ m^{-3}$	71 4 1 2022		
PRD	2014-2021/2022	RF	ERA5	$-1.81 \pm 2.14 \ \mu g \ m^{-3}$	Zheng et al., 2023		
SCB				$+12.24 \pm 4.07 \; \mu g \; m^{-3}$			
YRD				$+10.92 \pm 3.24 \ \mu g \ m^{-3}$			
Xiamen				+2.71 μg m ⁻³ yr ⁻¹			
Fuzhou	2015 2020	WZ MI D	ED A C	$+2.17~\mu g~m^{-3}~yr^{-1}$	T' + 1 2022		
Longyan	2015–2020	KZ-MLR	ERA5	$+0.76~\mu g~m^{-3}~yr^{-1}$	Ji et al., 2023		
Nanping				$+1.78~\mu g~m^{-3}~yr^{-1}$			
Northeast China		KZ-MLR	ERA5	+0.1688 μg m ⁻³ yr ⁻¹			
Liaoning	2012 2021			$-0.0864~\mu g~m^{-3}~yr^{-1}$	GI 1 2022		
Jilin	2013–2021			$+0.093~\mu g~m^{-3}~yr^{-1}$	Shang et al., 2023		
Heilongjiang				$+0.5562~\mu g~m^{-3}~yr^{-1}$			
Eastern China				+3.60 μg m ⁻³			
BTH	A 4 G 4 2012/2020	WDF CMAO	FNL	$+3.95~\mu g~m^{-3}$	1: 4 1 2022		
YRD	Apr to Sept, 2013/2020	WRF-CMAQ		$+3.91~\mu g~m^{-3}$	Liu et al., 2023		
FWP				$+7.75~\mu g~m^{-3}$			
Beijing				+0.52 ppb yr ⁻¹			
Chengdu	2012 2020			$+0.57~\mathrm{ppb~yr^{-1}}$	D 1 2022		
Guangzhou	2013–2020	Observation-based model	CMA	$+0.59 \text{ ppb yr}^{-1}$	Pan et al., 2023		
Shanghai				+0.62 ppb yr ⁻¹			
NCP	Nr. 1			−0.88 ppb			
FWP	May to Aug,	RegCM-Chem-YIBs	N/A	−1.41 ppb	Ma et al., 2023		
YRD	2008/2009–2013			−1.03 ppb			

Region/City	Study period	eriod Model Meteorological da		Meteorological impact	Reference	
PRD	May to Aug,			−0.23 ppb		
SCB	2008/2009–2013	_		−0.41 ppb		
NCP				−0.04 ppb		
FWP	N	RegCM-Chem-YIBs	N/A	−0.09 ppb	Ma et al., 2023	
YRD	May to Aug, 2008/2014–2018			−0.96 ppb		
PRD	2008/2014–2018			−1.08 ppb		
SCB				+0.71 ppb		
		GEOS-Chem		+0.26 ppb yr ⁻¹		
	Summer, 2015–2019	XGBoost		$+0.19~\mathrm{ppb~yr^{-1}}$		
NCP		Deep learning model	– MERRA2	+0.14 ppb yr ⁻¹	Wang et al., 2024	
NCP	Summer, 2019–2021	GEOS-Chem	— MERRA2	−0.74 ppb yr ⁻¹	wang et al., 2024	
		XGBoost		$-1.55~\mathrm{ppb~yr^{-1}}$		
		Deep learning model		$-1.74~\mathrm{ppb~yr^{-1}}$		
China	2015–2022	KZ-XGBoost	ERA5	Meteorology increased O ₃ .	Yao et al., 2024	
E (Cl.	2010/2021	GEOS-Chem	1.5500.10	–7.3 μg m ^{–3}	NT: 4 1 2024	
Eastern China	2019/2021	LightGBM	MERRA2	$-6.8~\mu\mathrm{g}~\mathrm{m}^{-3}$	Ni et al., 2024	
	2015–2022			Meteorology led a slight O ₃ increase.		
	Spring, 2015–2022			10102		
BTH	Summer, 2015–2022	XGBoost	ERA5	Meteorology increased O ₃ by 8.2 μg m ⁻³ /0.01	Luo et al., 2024	
	Autumn, 2015–2022			μg m ⁻³ /2.7 μg m ⁻³ in spring/summer/winter,		
	Winter, 2015–2022			and decreased O_3 by $-0.3~\mu g~m^{-3}$ in autumn.		
China	Summer, 2013–2022			$+0.2~\mu { m g}~{ m m}^{-3}~{ m yr}^{-1}$		
ВТН	2012 2012	MLR	ERA5	+0.9 μg m ⁻³ yr ⁻¹	Yan et al., 2024	
YRD	Summer, 2013–2019			$-0.3~\mu g~m^{-3}~yr^{-1}$		

Region/City	Study period	Model	Meteorological data	Meteorological impact	Reference	
BTH	G 2010 2021			$-3.9 \ \mu g \ m^{-3} \ yr^{-1}$		
YRD	Summer, 2019–2021	MLR	ERA5	$-4.1~\mu g~m^{-3}~yr^{-1}$	V . 1 2024	
ВТН	S 2021 2022	MLK	EKAS	+4.3 μg m ⁻³ yr ⁻¹	Yan et al., 2024	
YRD	Summer, 2021–2022			$+10.4~\mu g~m^{-3}~yr^{-1}$		
	2016–2023			Meteorology decreased (increased) O ₃ in		
	2010–2023			2016, 2020, 2021, 2023 (2017–2019, 2022).		
	Spring, 2016–2023			Meteorology decreased (increased) O ₃ in 2016,		
	Spring, 2010–2023			2018, 2021, 2023 (2017, 2019, 2020, 2022).		
YRD	Summer, 2016–2023	KZ-MLR	ERA5	Meteorology decreased (increased) O ₃ in	Hu at al. 2024	
TKD		KZ-MLK	EKAJ	2020, 2021, 2023 (2016–2019, 2022).	Hu et al., 2024	
	Autumn, 2016–2023			Meteorology decreased (increased) O ₃ in		
	Autumi, 2010–2023			2016–2017 (2018–2023).		
	Winter, 2016–2023	Winter 2016 2022			Meteorology decreased (increased)O ₃ in	
				2018-2020,2022(2016,2017,2021,2023).		
	Spring, 2014/2020			−0.89 ppb		
YRD	Summer, 2014/2020	WRF-Chem	FNL	+0.23 ppb	Li et al., 2024	
TKD	Autumn, 2014/2020	wkr-chem	FNL	−2.74 ppb	Li et al., 2024	
	Winter, 2014/2020			−3.86 ppb		
PRD	Spring, 2013–2022	MLR	ERA5	+0.88 ppb yr ⁻¹	Cao et al., 2024	
YRD	2015–2022	KZ-MLR	ERA5	The meteorological impacts account for an	W	
IKD	2013-2022	NZ-WILK ERAS		average of 71.8% of O ₃	Wu and An, 2025	

⁷⁸ a Symbol "—" means the continuous study period from the start year to the end year (left of —) to the end year (right of —); Symbol "/" means the discrete study period.

^b The meteorological impact expressed by ppb yr^{-1} or $μg m^{-3} yr^{-1}$ means the trend from the start to end year of the study period. Meteorological impact expressed by ppb, $μg m^{-3}$ or % means the difference between the end year and start year (end year – start year).

Table S2. Summary of the meteorological variables from the ERA5, MERRA2, FNL and FNL025 reanalysis dataset used to establish MLR models.

Abbreviations	Description	Meteorological Dataset
SLP	Daily mean sea level pressure (hPa)	ERA5, MERRA2, FNL, FNL025
TCCday	Total cloud area fraction (%) averaged over 08:00 to 17:00 LT	ERA5, MERRA2
PBLHday	Planetary boundary layer height (m) averaged over 08:00 to 17:00 LT	ERA5, MERRA2, FNL, FNL025
U10	Daily mean 10-meter eastward wind (m s ⁻¹)	ERA5, MERRA2, FNL, FNL025
V10	Daily mean 10-meter northward wind (m s ⁻¹)	ERA5, MERRA2, FNL, FNL025
T2max	Daily maximum 2-meter air temperature (°C)	ERA5, MERRA2, FNL, FNL025
SSRDday	Surface incoming shortwave flux (W m ⁻²) averaged over 08:00 to 17:00 LT	ERA5, MERRA2
TP	Total precipitation (mm day ⁻¹)	ERA5, MERRA2
PWAT	Daily mean precipitable water considered as a single layer (mm)	FNL, FNL025
RH2	Daily mean 2-meter relative humidity (%)	ERA5, MERRA2, FNL, FNL025
V850	Daily mean northward wind at 850 hPa (m s ⁻¹)	ERA5, MERRA2, FNL, FNL025

Table S3. The 10-year trend in each meteorological factor used to establish MLR models from the ERA5, MERRA2, and FNL during four seasons.

Season	Dataset	RH2 (% yr ⁻¹)	U10 (m s ⁻¹ yr ⁻¹)	V10 (m s ⁻¹ yr ⁻¹)	SSRDday (W m ⁻² yr ⁻¹)	PBLHday (m yr ⁻¹)	TCCday (% yr ⁻¹)	TP (mm day ⁻¹ yr ⁻¹) or PWAT (mm yr ⁻¹)	SLP (hPa yr ⁻¹)	T2max (°C yr ⁻¹)	V850 (m s ⁻¹ yr ⁻¹)
	ERA5	+0.08	+0.01	-0.00	+0.68	+3.89	+0.00	-0.02	-0.02	+0.18	-0.01
Spring	MERRA2	+0.33	+0.01	-0.00	+1.59	+5.54	+0.24	+0.02	-0.08	+0.16	+0.00
	FNL	+0.12	+0.01	-0.01	/	+14.44	/	+0.20	-0.09	+0.12	-0.01
	ERA5	+0.18	-0.00	+0.01	-0.72	-2.10	+0.18	+0.03	+0.02	+0.08	+0.03
Summer	MERRA2	+0.35	+0.00	+0.03	+1.11	-6.95	+0.29	-0.03	-0.04	+0.04	+0.05
	FNL	+0.29	-0.00	+0.01	/	+4.96	/	+0.23	-0.08	-0.01	+0.05
	ERA5	-0.17	+0.01	-0.02	-1.62	+0.04	-0.21	-0.04	+0.21	-0.10	-0.05
Autumn	MERRA2	+0.11	+0.00	-0.03	-0.99	-2.52	-0.17	-0.06	+0.17	-0.12	-0.04
	FNL	-0.29	+0.00	-0.03	/	+6.66	/	-0.15	+0.13	-0.16	-0.05
	ERA5	+0.07	+0.00	-0.00	-0.03	+2.71	+0.41	+0.00	+0.04	+0.02	+0.03
Winter	MERRA2	+0.36	-0.01	-0.01	+0.68	+5.29	+0.31	+0.01	+0.00	+0.04	+0.04
	FNL	+0.15	-0.01	-0.01	/	+8.68	/	+0.12	-0.03	+0.01	+0.03

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