

Article

Contrasting Responses of Peak Summer Surface Ozone to Anthropogenic Emission Changes Across Two Major Emission Hotspots in Eastern China

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Abstract

Peak summer surface ozone (O₃) threatens human health, crop productivity, and ecosystem stability in eastern China, but similar O₃ trends may reflect contrasting anthropogenic drivers. Using the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem) and the Multi-Resolution Emission Inventory for China (MEIC), we examined July maximum daily 8 h average (MDA8) O₃ over the Bohai Plain and the Yangtze River Delta (YRD) from 2014 to 2020. Emission substitutions under fixed 2014 meteorology isolated the O₃ responses to changes in total emissions and individual pollutants. Although O₃ levels were high in both regions by 2019 and declined sharply in 2020, the two regions showed opposite responses to emission changes. Over the Bohai Plain, substituted inventories reduced MDA8 O₃ in all later scenarios, with a 4.57 ppb decrease for the 2020 inventory. Over the YRD, emission changes increased O₃ by up to 4.70 ppb. VOC substitution produced the largest decrease over the Bohai Plain at 5.46 ppb, whereas substituting 2020 NO_x emissions increased YRD O₃ by 4.22 ppb. The joint NO_x and VOC substitution increased YRD O₃ by 4.97 ppb, revealing a nonadditive response. Formation sensitivity also diverged, with the western Bohai Plain shifting toward VOC-sensitive conditions and NO_x sensitivity strengthening in the northern YRD. These results show that similar peak summer O₃ evolution can conceal fundamentally different emission responses. These findings support region-specific multipollutant control strategies for the two regions.

Keywords: near surface ozone; emission hotspots; anthropogenic emissions; emission substitution; ozone sensitivity



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1. Introduction

Surface ozone (O₃) is a secondary air pollutant formed through photochemical reactions involving precursor compounds in the presence of sunlight, and its environmental impacts are closely linked to regional development patterns [1]. Elevated O₃ not only increases health risks, including respiratory inflammation and cardiovascular impairment [2,3] but also suppresses plant photosynthesis and damages chlorophyll structure, thereby causing irreversible impacts on crop yields and ecosystem stability [4,5]. O₃ has therefore become a key environmental constraint on regional sustainable development. Since the Air Pollution Prevention and Control Action Plan was implemented in 2013, China has achieved substantial reductions in sulfur dioxide (SO₂), nitrogen oxides (NO_x), and fine particulate matter (PM_{2.5}). However, near-surface O₃ has shown a contrasting

upward trend and has replaced PM_{2.5} as the primary pollutant in summer in most cities [6]. At the regional scale, the annual mean O₃ concentration across major Chinese urban agglomerations increased by 2.49 µg m⁻³ during 2013 to 2020, with particularly pronounced increases over major emission-intensive regions in eastern China, including the North China Plain and the Yangtze River Delta (YRD) [7]. Summertime represents a particularly important period for evaluating the effects of anthropogenic emission changes on surface O₃ because high temperature and strong solar radiation accelerate radical cycling and the photochemical oxidation of VOCs and CO in the presence of NO_x. Analyses combining national monitoring observations with chemical transport models have shown that changes in anthropogenic emissions made substantial contributions to the summertime O₃ increase in eastern China after 2013, although meteorological variability also played an important role [6,8,9]. For central-eastern China, July-specific simulations further attributed a regionally averaged MDA8 O₃ increase of approximately 4.0 ± 1.9 ppbv between 2003 and 2015 to emission changes [10]. These findings demonstrate the importance of evaluating O₃ responses to changing anthropogenic emissions under active photochemical conditions during peak summer, when inappropriate precursor controls may produce particularly pronounced and nonlinear responses.

The nonlinear response of O₃ to its precursors remains a major challenge for effective O₃ mitigation [11]. Existing studies have shown that NO_x and volatile organic compounds (VOCs) are the primary precursors, and their relative abundances directly determine O₃ production rates and peak levels [12]. Reducing a single precursor can restructure chemical equilibria and trigger an O₃ rebound. For example, O₃ increased in Beijing during 2000 to 2006 when NO_x emissions declined but VOCs emissions increased [13], and O₃ pollution intensified in Shanghai in 2009 following decreases in NO_x concentrations [14]. These cases underscore the complexity of O₃ control. In addition, carbon monoxide (CO), ammonia (NH₃), SO₂, and PM_{2.5}, although not canonical O₃ precursors, can indirectly regulate O₃ formation by altering photochemical reaction efficiency and atmospheric oxidizing capacity [15], which further complicates regional O₃ mitigation.

The Bohai Plain and the YRD are two major emission hotspots in eastern China, where dense urban, industrial, power, transport, residential, and agricultural activities coexist within connected regional environments. Surface O₃ in both regions is regulated by interactions among anthropogenic and natural emissions, local photochemistry, and regional transport. Observational and modeling studies have shown that urban plumes, combustion-related emissions, soil NO_x, and transported precursors can jointly affect O₃ production across eastern China [16–18]. The two regions were selected as a focused comparative pair because they combine a common policy and temporal context with scientifically informative regional contrasts. Both underwent substantial multipollutant emission changes during the national clean air actions from 2014 to 2020, and observations documented significant summertime O₃ increases over both the broader North China Plain and the YRD during much of this period [9]. At the same time, the two regions differ in latitude, monsoonal and coastal influences, source composition, precursor emission trajectories, regional transport, and evolving O₃ formation sensitivity [19–21]. These commonalities and contrasts provide a focused basis for examining whether shared broad features in July O₃ evolution can arise from different responses to changes in the multipollutant emission mixture.

Previous studies have demonstrated substantial spatial and temporal differences in O₃ formation sensitivity across China [19–21], as well as regional differences in O₃ responses to emission changes and control measures [8,15]. Other studies have separated and quantified the respective contributions of anthropogenic emissions and meteorological variability to recent O₃ changes [6,8]. However, the regional implications of the combined evolution of multiple anthropogenic emissions remain less well understood. Similar temporal variations

in O_3 do not necessarily indicate similar emission-related responses because the effects of emission changes depend strongly on regional precursor balance and chemical sensitivity. A direct comparison of the Bohai Plain and the YRD within a consistent modeling framework therefore provides an opportunity to examine how evolving emission mixtures produce different regional O_3 responses and to identify the factors underlying these differences.

In this study, we used WRF-Chem and annual MEIC inventories to investigate July MDA8 O_3 over the Bohai Plain and the YRD from 2014 to 2020. Within each regional domain, meteorological conditions were fixed at their July 2014 state while the complete anthropogenic emission inventory was replaced year by year. Additional experiments separately substituted NO_x , VOCs, SO_2 , CO, NH_3 , primary particulate matter, and the combination of NO_x and VOC emissions. Accordingly, the objectives were to (1) characterize the baseline spatial and temporal evolution of peak summer O_3 in the two regions, (2) quantify and compare their responses to changes in the complete anthropogenic emission mixture under a fixed meteorological background, and (3) identify the individual pollutant changes associated with the regional contrast and examine the roles of precursor balance, O_3 formation sensitivity, and the nonadditive response to combined NO_x and VOC changes. The principal contribution of this study is the use of a consistent experimental framework across two major emission hotspots that combines annual complete inventory substitutions with controlled individual pollutant and joint NO_x and VOC substitutions. This framework reveals that shared broad features in peak summer surface O_3 evolution can coexist with opposite responses to anthropogenic emission changes and clarifies the emission and chemical conditions associated with this regional divergence.

2. Materials and Methods

2.1. Study Area

The Bohai Plain and the YRD were selected as two major emission hotspots in eastern China (Figure 1). The Bohai Plain covers Beijing, Tianjin, central and southern Hebei, and northern Shandong. The YRD domain covers Shanghai and major parts of Jiangsu, northern Zhejiang, and eastern Anhui.

Both regions contain major urban agglomerations, industrial centers, transport corridors, power and residential sources, and extensive surrounding nonurban areas, but they differ in geographic setting and emission structure. The Bohai Plain includes inland urban and industrial centers together with broad nonurban areas surrounding the Bohai Sea. The YRD contains a denser coastal network of industrial, port, transport, and urban sources. Together, the shared policy period and the contrasting source, geographic, and chemical characteristics make the two domains a focused comparative pair for evaluating region-dependent O_3 responses under a consistent emission substitution framework.

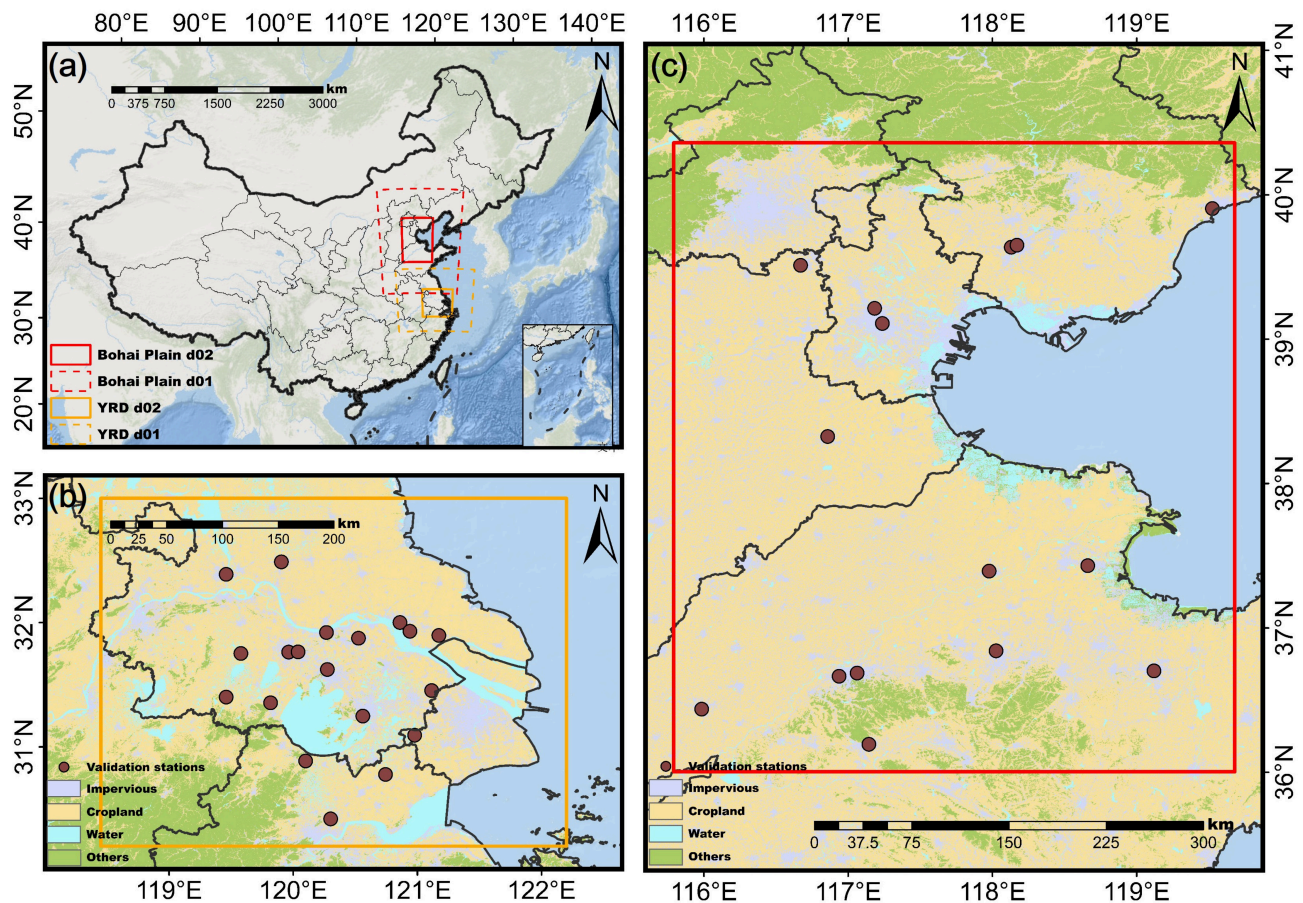


Figure 1. Study areas and modeling domains. (a) Locations of the separate outer domains (d01; 30 km horizontal grid spacing) and inner domains (d02; 10 km horizontal grid spacing) configured for the Bohai Plain and the Yangtze River Delta (YRD). Dashed and solid rectangles indicate the outer and inner domains, respectively. (b,c) Land cover distributions and surface monitoring stations used for model evaluation within the YRD and Bohai Plain inner domains, respectively. Land cover was derived from the 2014 China Land Cover Dataset (CLCD) at a spatial resolution of 30 m and reclassified into impervious surfaces, cropland, water, and other land types [22].

2.2. Data Source

2.2.1. Meteorological Data

We used the ERA5 reanalysis produced by the Copernicus Climate Change Service of the European Center for Medium-Range Weather Forecasts [23,24] to evaluate the meteorological fields simulated by WRF-Chem. ERA5 provides hourly data at a spatial resolution of $0.25^\circ \times 0.25^\circ$ and includes multidimensional atmospheric, land, and ocean variables from 1979 to the present (available from the Copernicus Climate Data Store at <https://cds.climate.copernicus.eu/> (accessed on 6 September 2026)). In this study, we extracted July data for 2014 to 2020, including wind speed, relative humidity, and 2 m air temperature, and compared these variables with the corresponding WRF-Chem simulations. Using the same ERA5 data source described above, we assessed whether the July 2014 meteorological background was markedly anomalous within 2014–2020. Regional values of 2 m air temperature, 10 m wind speed, total precipitation, and surface solar radiation downwards were calculated for the same simulation period using ERA5 grid cells within each d02 boundary and cos(latitude) weighting. Wind speed was calculated from hourly U10 and V10 before averaging. The July 2014 anomalies were standardized relative to the corresponding 2014–2020 means and sample standard deviations.

The meteorological initial and boundary conditions were generated from the Final Operational Global Analysis reanalysis provided by the National Centers for Environmental Prediction. This dataset has a horizontal resolution of 0.25° and a temporal resolution of 6 h, and was used to provide the large-scale meteorological background for the model.

Radiosonde observations were used to complement the surface evaluation by examining the vertical structures of air temperature, specific humidity, and wind speed in the lower troposphere [25]. Radiosonde observations were obtained from the quality-controlled Integrated Global Radiosonde Archive version 2.2 (IGRA 2.2) [26]. All IGRA stations located within the two WRF-Chem inner domains and reporting during the analysis period were included. These stations comprised Beijing and Zhangqiu in the Bohai Plain and Nanjing, Shanghai (Baoshan), and Hangzhou in the YRD. All available 00 and 12 UTC soundings from July 2014 were retained, yielding 120 profiles over the Bohai Plain and 180 profiles over the YRD. Each sounding was paired with simultaneous output from the nearest 10 km WRF-Chem grid cell. Modeled air temperature was calculated from perturbation potential temperature and full pressure; specific humidity was derived from QVAPOR, and wind speed was calculated from destaggered U and V components after rotation to Earth-relative coordinates. Observed specific humidity was derived from pressure, temperature, and relative humidity. Both observed and modeled variables were linearly interpolated to common heights between 0.10 and 3.00 km above ground level. No stations or sounding times were selected according to model performance.

2.2.2. Emissions Inventory Data

We constructed the anthropogenic emission inventory using the Multi-resolution Emission Inventory for China (MEIC; available at <http://meicmodel.org.cn/> (accessed on 6 September 2026)). MEIC provides emissions at a horizontal resolution of $0.25^\circ \times 0.25^\circ$ and covers five major sectors, including industry, residential, agriculture, power generation, and transportation. This inventory captures the spatiotemporal characteristics of anthropogenic emissions in the study regions and provides emission inputs for the model simulations.

2.2.3. Pollutant Observation Data

Observed pollutant concentrations were obtained from the China National Environmental Monitoring Center (CNEMC) through the National Urban Air Quality Real Time Distribution Platform (available at <https://air.cnemc.cn:18007/> (accessed on 1 September 2026)). The dataset includes hourly observations of $\text{PM}_{2.5}$, SO_2 , NO_2 , and O_3 . These observations were used as a reference to evaluate the accuracy of simulated chemical species and the reasonableness of aerosol components.

To place the July simulations in seasonal context, we analyzed the monthly 1 km ground-level MDA8 O_3 product from the ChinaHigh O_3 product (Version 3) during 2014–2020 [7,27]. The product combines ground observations, satellite data, atmospheric reanalysis, emission information, and model simulations. For each region, valid land grid cells within the native WRF-Chem d02 boundary were averaged using $\cos(\text{latitude})$ weighting. The seven-year mean and sample standard deviation were then calculated for each calendar month.

Surface O_3 observations were obtained from 34 CNEMC monitoring stations, including 15 stations in the Bohai Plain and 19 stations in the YRD (Figure 1b,c). The surrounding environments of the monitoring stations were characterized using the impervious surface fraction derived from the 2014 China Land Cover Dataset, adapting the land cover-based assessment approach of He et al. [28]. Of the 34 stations, 27 were located in predominantly urban settings, while the remaining seven were situated in less urbanized peripheral settings. The impervious surface fractions surrounding the stations ranged from 7.5% to

99.0%, indicating that the monitoring network sampled a broad gradient of urbanization and included both urban and suburban environments, although urban settings were more strongly represented. Detailed station-level information, including station identifiers, coordinates, impervious-surface fractions, and surrounding land-cover contexts, is provided in Table A1.

2.3. WRF-Chem Model Configuration

The WRF-Chem model couples the Weather Research and Forecasting meteorological model with the Chem chemical module. This integrated model can simulate and predict physical quantities such as temperature, wind fields, cloud and precipitation processes, as well as the concentration, diffusion, and interactions of gases such as particulate matter and O₃. The model has demonstrated significant accuracy and reliability, particularly in O₃ predictions [29].

In this study, WRF-Chem version 3.9.1 was used to simulate the effects of anthropogenic emission changes on O₃ concentrations over the Bohai Plain and the YRD. The simulations were conducted for July of each year from 2014 to 2020 using two independent regional domain configurations for the Bohai Plain and the Yangtze River Delta (YRD). Each regional configuration employed a Lambert conformal projection and consisted of a two-way nested outer domain (d01) with a horizontal grid spacing of 30 km and an inner domain (d02) with a grid spacing of 10 km. For the Bohai Plain, d01 and d02 contained 30 × 39 and 34 × 49 WRF namelist grid points, corresponding to projected horizontal spans of approximately 870 × 1140 km and 330 × 480 km, respectively. For the YRD, d01 and d02 contained 31 × 26 and 37 × 34 grid points, corresponding to approximately 900 × 750 km and 360 × 330 km, respectively. Both regional configurations used 30 terrain-following model layers bounded by 31 vertical interfaces, extending from the surface to a model top pressure of 50 hPa. The boundaries of the outer and inner domains for the two regional configurations are shown separately in Figure 1. Chemical initial and boundary conditions were provided by the CAM-Chem model, while biogenic emissions were derived from the MEGAN version 2.1 (Model of Emissions of Gases and Aerosols from Nature). Studies have shown that the CBM-Z mechanism for gas phase reactions (Carbon Bond Mechanism version Z) exhibits enhanced oxidative capacity, thereby improving the kinetic representation of O₃ [30]. Consequently, this study employed CBM-Z chemistry in the gas phase during the simulations, while the MOSAIC model was used for aerosol mechanisms. The detailed physical and chemical parameterization schemes are presented in Table 1.

Table 1. Physical and chemical parameterization schemes used in the WRF-Chem simulations.

No.	Physicochemical Parameter Options	Scheme
1	Microphysics	Purdue Lin [31]
2	Shortwave radiation	Goddard [32]
3	Longwave radiation	RRTMG [33]
4	Land surface	NOAH [34]
5	Surface layer	Revised MM5 Monin-Obukhov scheme
6	Planetary boundary layer	Yonsei University Scheme (YSU) [35]
7	Cumulus	Kain-Fritsch [36]
8	Gas-phase mechanism	CBMZ
9	Aerosol module	4-bin MOSAIC aerosol with VBS [37]
10	Photolysis scheme	Madronich photolysis (TUV) [38]

The physical and chemical parameterizations were selected as a consistent configuration to represent the cloud, radiation, land surface, boundary layer, and atmospheric chemistry processes relevant to regional summertime O₃ simulations at horizontal grid

spacings of 30 and 10 km. The Purdue Lin microphysics scheme explicitly represents mixed-phase cloud and precipitation processes, while the Kain–Fritsch cumulus scheme accounts for convective transport that is not fully resolved at these grid spacings. The Goddard shortwave and RRTMG longwave schemes were used to represent atmospheric radiative transfer and the surface radiation budget, which influence surface heating and boundary layer development. Surface exchange and turbulent mixing were represented through the coupled use of the Noah land surface model, the Revised MM5 Monin–Obukhov surface layer scheme, and the YSU planetary boundary layer scheme. Noah calculates soil states and surface energy and moisture fluxes, the Revised MM5 scheme determines surface exchange coefficients, and YSU represents nonlocal turbulent mixing and entrainment at the top of the planetary boundary layer [34,35,39]. The selection of YSU is further supported by a systematic evaluation covering several regions of China, including the North China Plain and the YRD, which found that YSU provided competitive performance for 10 m wind simulations, although scheme performance varied with region, season, meteorological variable, and vertical range [40]. Gas phase oxidation and O₃ chemistry were represented using CBM-Z, while the 4-bin MOSAIC aerosol module with VBS described aerosol composition, size-resolved processes, and the gas particle partitioning of semivolatile organic compounds. The Madronich TUV scheme provided the photolysis rates required by the chemical mechanism. The same configuration was applied consistently in both nested domains and throughout all baseline and emission substitution simulations. While this configuration provides a consistent basis for the emission substitution experiments, it is not regarded as uniquely optimal because parameterization performance may vary with region, season, meteorological variable, and vertical range.

2.4. Experiment Design

To systematically examine regional O₃ responses to changes in anthropogenic emissions, we designed three groups of simulations. July was selected to examine regional O₃ responses under peak summer photochemical conditions in eastern China. In this study, peak summer refers to a midsummer period characterized by elevated O₃ concentrations and active photochemistry rather than to the single calendar month with the absolute annual maximum O₃ concentration. High temperatures and strong solar radiation during this period promote rapid radical cycling, precursor oxidation, and O₃ production. Sun et al. [10] used July simulations to investigate the respective effects of anthropogenic emissions and meteorology on summertime O₃ changes over central eastern China, supporting the use of July as an informative midsummer analysis window. Li et al. [9] further identified rising temperatures in June and July as a major meteorological contributor to the recent summertime O₃ increase over the North China Plain. For the YRD, Yang et al. [41] identified July 2017 as the month with the most severe O₃ pollution during 2013–2020 and attributed this event primarily to enhanced chemical production under hot and dry conditions. The North China Plain has also been identified as a major hotspot where high temperatures intensify warm-season O₃ pollution [42]. Together, these studies support the use of July as an informative period for examining peak summer O₃ responses in both regions. The 2014–2020 annual cycles further show that July falls within the high O₃ season in both regions, although it is not the unique annual maximum in both regions (Figure A1). Using the same calendar month across the simulations also provides a consistent seasonal basis for comparison. However, conditions during other warm season months can differ in meteorology, natural emissions, and chemical sensitivity, and this broader seasonal variability is not captured by the present analysis.

2.4.1. Baseline Simulations

We simulated July MDA8 O₃ over the Bohai Plain and the YRD for each year from 2014 to 2020 using year-specific meteorological fields and the corresponding MEIC anthropogenic emissions (Table 2). These baseline simulations were used to characterize the spatiotemporal variability of O₃ under the combined influences of meteorology and anthropogenic emissions and to provide reference information for the subsequent sensitivity experiments.

Table 2. WRF-Chem simulation experiments.

Type	Experiment	Meteorology	MEIC Anthropogenic Emissions
Baseline	S14AE14	July 2014	2014
	S15AE15	July 2015	2015
	S16AE16	July 2016	2016
	S17AE17	July 2017	2017
	S18AE18	July 2018	2018
	S19AE19	July 2019	2019
	S20AE20	July 2020	2020
Total emission substitution	S14AE15	July 2014	2015
	S14AE16		2016
	S14AE17		2017
	S14AE18		2018
	S14AE19		2019
	S14AE20		2020
Individual pollutant substitution	S14AE14_withNO _x 20	July 2014	2014 except 2020 NO _x
	S14AE14_withVOCs20		2014 except 2020 VOCs
	S14AE14_withSO ₂ 20		2014 except 2020 SO ₂
	S14AE14_withCO20		2014 except 2020 CO
	S14AE14_withNH ₃ 20		2014 except 2020 NH ₃
	S14AE14_withPM20		2014 except 2020 PM
	S14AE14_withNO _x VOCs20		2014 except 2020 NO _x and VOCs

Note: “S” denotes the simulation year, and “AE” represents anthropogenic emissions. In the baseline simulations, both meteorological fields and MEIC anthropogenic emissions correspond to the same year. For example, S20AE20 represents the July 2020 simulation using 2020 meteorology and 2020 MEIC anthropogenic emissions. In the total emission substitution experiments, meteorology was fixed at July 2014 conditions, while the full MEIC anthropogenic emission inventory was replaced by inventories from 2015 to 2020. In the individual pollutant substitution experiments, meteorology and all non-target pollutant emissions were kept at 2014 levels, while only the target pollutant emissions were replaced by their 2020 MEIC values.

2.4.2. Simulations of the Total Anthropogenic Emission Effect

To quantify the effects of changes in the complete anthropogenic emission mixture, we designed a series of emission substitution experiments based on the 2014 baseline simulation, S14AE14. The year 2014 was selected because it is the first year of the analysis period and therefore provides a common reference state for evaluating all subsequent emission inventories. The purpose of using 2014 meteorology is not to treat this year as a climatological average. Rather, keeping the meteorological background constant ensures that every annual inventory is evaluated under the same temperature, radiation, humidity, boundary layer, circulation, and transport conditions. In these experiments, the meteorological conditions were fixed at their July 2014 values, while the complete MEIC anthropogenic emission inventory was replaced successively with the inventories for 2015 to 2020. Differences from S14AE14 therefore quantify the O₃ responses associated with changes in the prescribed anthropogenic emissions after removing the influence of interannual meteorological variability. Similar factorial and baseline substitution designs

have been used to separate emission and meteorological influences on surface O₃ and to evaluate the effects of changes in individual pollutant emissions [10,15].

2.4.3. Simulations of Individual Pollutant Emission Effects

To quantify O₃ responses to changes in different anthropogenic pollutants, we conducted a set of controlled experiments using S14AE14 as the reference. In each experiment, emissions of all pollutants other than the target species were held at 2014 MEIC levels, and only the target pollutant was replaced with its 2020 MEIC emissions. We performed this procedure for NO_x, VOCs, SO₂, NH₃, CO, PM, and the combined NO_x and VOCs substitution. Comparison with S14AE14 quantified the O₃ response to each individual emission change and identified the pollutants most strongly associated with the contrasting regional responses.

2.5. Model Evaluation Metrics

To comprehensively evaluate model performance in simulating meteorological fields and air pollutant concentrations, we quantified model biases by computing a set of statistical metrics based on comparisons between simulations and observations. The evaluation metrics are described below.

2.5.1. Metrics for Meteorological Variables

We used root mean square error (RMSE), the correlation coefficient (R), mean bias (MB), normalized mean bias (NMB), normalized mean error (NME), and the index of agreement (IOA) to evaluate meteorological variables, including temperature, relative humidity, and wind speed. NMB and NME help reduce potential evaluation bias caused by wide ranges in observed values, and IOA is used to quantify the overall agreement between simulations and observations.

2.5.2. Metrics for Pollutant Concentrations

In addition to MB, NMB, R, and IOA, we used mean fractional error (MFE) and mean fractional bias (MFB) as core metrics for particulate matter and related pollutants. Following the chemical transport model performance criteria proposed by Boylan and Russell [43], model performance is considered acceptable when MFB is between negative 60% and 60%, and MFE is less than or equal to 75%. Performance is considered excellent when MFB is between negative 30% and 30%, and MFE is less than or equal to 50%. To further assess whether the model captured the observed interannual variability, annual July mean O₃ concentrations were calculated at nine representative monitoring stations in each region using valid paired hourly observations and corresponding model values. The stations were selected to provide broad spatial coverage and relatively complete paired records during 2014–2020. The observed and modeled station-level series are presented in Figures A2 and A3.

3. Results

3.1. Model Validation

To ensure the reliability and robustness of the subsequent analyses, we evaluated WRF-Chem performance for meteorological fields and air pollutant concentrations. Model skill was quantified using multiple metrics, including root mean square error (RMSE), correlation coefficient (R), mean bias (MB), and normalized mean bias (NMB), to confirm that agreement between simulations and observations was sufficient for the analyses that follow.

Overall, WRF-Chem reproduced the temporal variability of 2 m air temperature (T2) and 2 m relative humidity (RH2) well, whereas its performance for 10 m wind speed (W10) was comparatively weaker (Figure 2). Over the Bohai Plain, T2 was slightly overestimated, with MB ranging from 0.94 to 1.65 K, while RH2 was slightly underestimated, with MB ranging from -10.14 to -5.62 percentage points. Both variables met the performance criteria of absolute NMB less than or equal to 15% and NME less than or equal to 25%. The correlations were also high, with R values ranging from 0.93 to 0.97 for T2 and from 0.89 to 0.95 for RH2, indicating that the model captured their temporal variability well. The performance for W10 was weakest, with positive NMB values ranging from 43% to 57% and IOA values ranging from 0.51 to 0.74. Simulated wind speeds were generally higher than the observations. The positive bias may reflect the combined influence of topographic smoothing and unresolved land-surface heterogeneity at the 10 km grid spacing, together with the representation of surface exchange and vertical momentum mixing in the surface-layer and planetary-boundary-layer schemes [39,40,44]. Nevertheless, the W10 correlations ranged from 0.55 to 0.84, indicating that the model captured the broad temporal variation in wind speed, although its magnitude was generally overestimated.

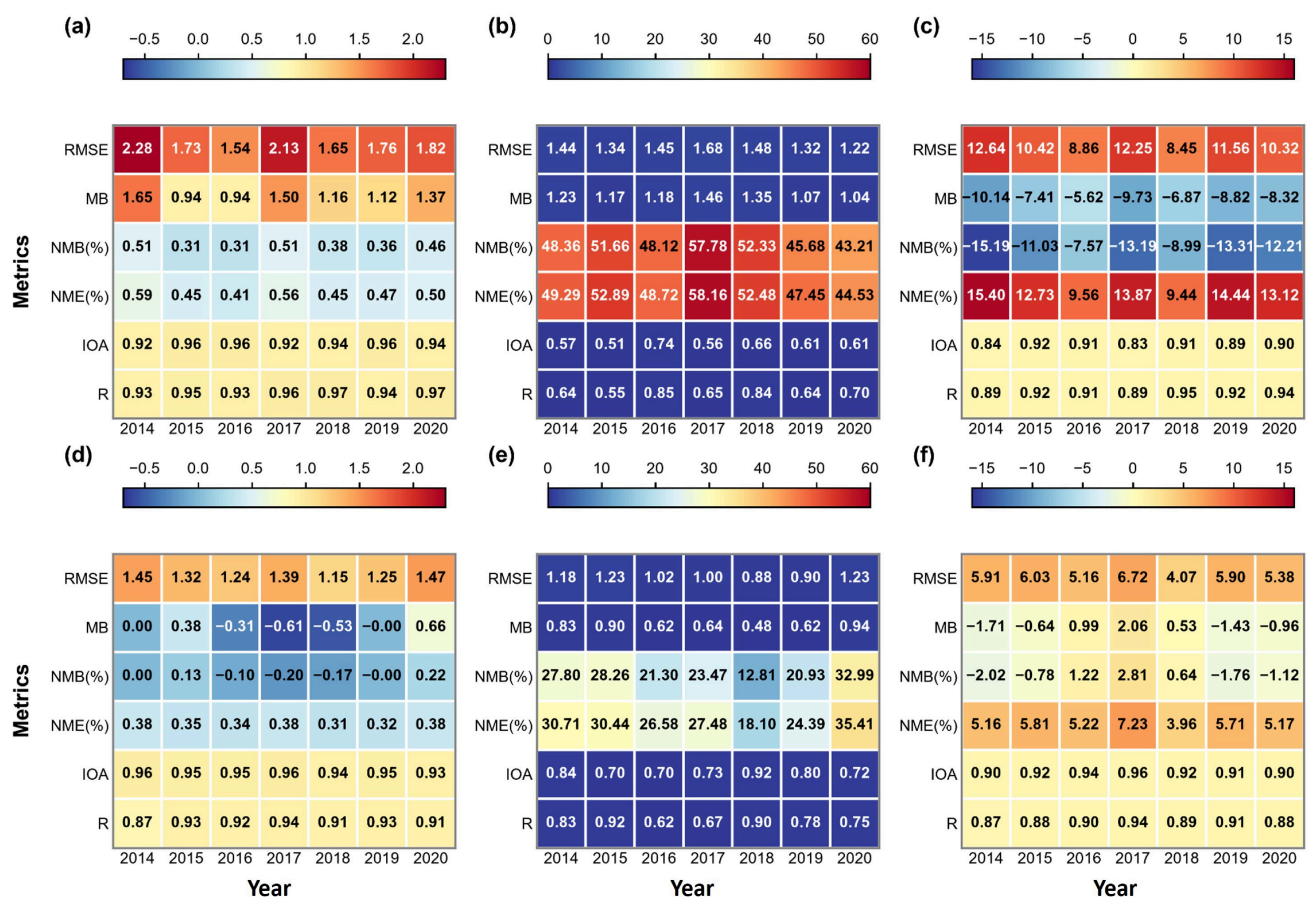


Figure 2. Model evaluation statistics for meteorological variables in the Bohai Plain (a–c) and the YRD (d–f). (a) T2 (K); (b) W10; (c) RH2 (%); (d) T2 (K); (e) W10; (f) RH2 (%).

Meteorological performance over the YRD differed slightly from that over the Bohai Plain. T2 and RH2 were mildly underestimated in most years, and W10 was overestimated, with MB ranging from 0.48 to 0.94 m s⁻¹. In terms of quantitative metrics, RMSE, MB, NMB, and NME were generally smaller in magnitude than those over the Bohai Plain, suggesting better meteorological performance over the YRD. This difference may be related

to more homogeneous land surface conditions and more stable meteorological fields in the region.

To complement the surface meteorological evaluation and examine the vertical structure of the wind speed bias, the lower troposphere was further evaluated using independent IGRA radiosonde profiles (Figure A4). Across 0.1–3.0 km AGL, the model reproduced the observed vertical variations in air temperature and specific humidity reasonably well. For air temperature, MB, RMSE, R, and IOA were 1.02 °C, 2.07 °C, 0.97, and 0.98, respectively, over the Bohai Plain, and 0.04 °C, 1.20 °C, 0.97, and 0.99 over the YRD. For specific humidity, the corresponding values were -0.21 g kg^{-1} , 2.28 g kg^{-1} , 0.83, and 0.90 over the Bohai Plain and -0.16 g kg^{-1} , 1.67 g kg^{-1} , 0.91, and 0.95 over the YRD. The wind-speed bias showed a pronounced dependence on height. Within 0.1–1.0 km AGL, WRF-Chem overestimated wind speed, with MB values of 2.07 and 1.40 m s^{-1} and NMB values of 45.5% and 29.6% over the Bohai Plain and the YRD, respectively. In contrast, the wind-speed biases within 1.5–3.0 km AGL decreased to -0.35 and -0.06 m s^{-1} , respectively. These results show that the model reproduced the principal thermodynamic profile structures, whereas the positive wind-speed bias was concentrated mainly in the lower atmosphere rather than representing a uniform overestimate throughout the lower troposphere.

Separately, the July 2014 meteorological background was compared with the corresponding July conditions during 2014–2020 (Figure A5). In 2014, all meteorological indicators for the two regions were close to their average values for the period 2014–2020. The standardized anomalies of T2, W10, TP, and SSRD were -0.14 , 0.55, -0.69 , and 0.63 over the Bohai Plain and -0.46 , -0.29 , 0.31, and -0.36 over the YRD, respectively. All absolute standardized anomalies were below 1. In 2014, all meteorological indicators for the two regions were close to their average values for the period 2014–2020. July 2014 therefore did not show a marked departure from the 2014–2020 distributions of the four examined regional mean indicators.

Model performance for air pollutant concentrations was generally strong, with biases within reasonable ranges and high indices of agreement, and O_3 was simulated most accurately (Figure 3). For O_3 , R ranged from 0.74 to 0.91 in the two regions, while MB ranged from -23.7 to $4.3 \mu\text{g m}^{-3}$. The observed and modeled July mean series at representative stations in each region provide additional information on interannual model performance (Figures A2 and A3). At most of the selected stations in both regions, the modeled concentrations generally captured the broad observed year-to-year variations, although O_3 was underestimated in most years. The agreement was stronger over the YRD and relatively weaker over the Bohai Plain. Nevertheless, the model over the Bohai Plain reproduced many of the observed increases and decreases, although the magnitude of the changes differed in some years. The relatively high observed concentrations at several Bohai Plain stations in 2019 and 2020 were underestimated by the model.

The interannual variation in O_3 bias likely reflects the combined influence of multiple meteorological and chemical processes. The persistent positive bias in W10 may affect simulated O_3 through changes in dispersion and transport, but its relatively limited variation among years cannot by itself explain the generally more negative O_3 bias after 2016. Previous studies have shown that O_3 variability over eastern China is jointly affected by meteorological conditions, background contributions, and anthropogenic emissions, while WRF-Chem simulations are also sensitive to the representation of precursor emissions [9,45,46]. Uncertainties in the representation of meteorological processes, precursor emission magnitude and chemical speciation, nonlinear chemistry, and regional transport may therefore have contributed to the changing model bias.

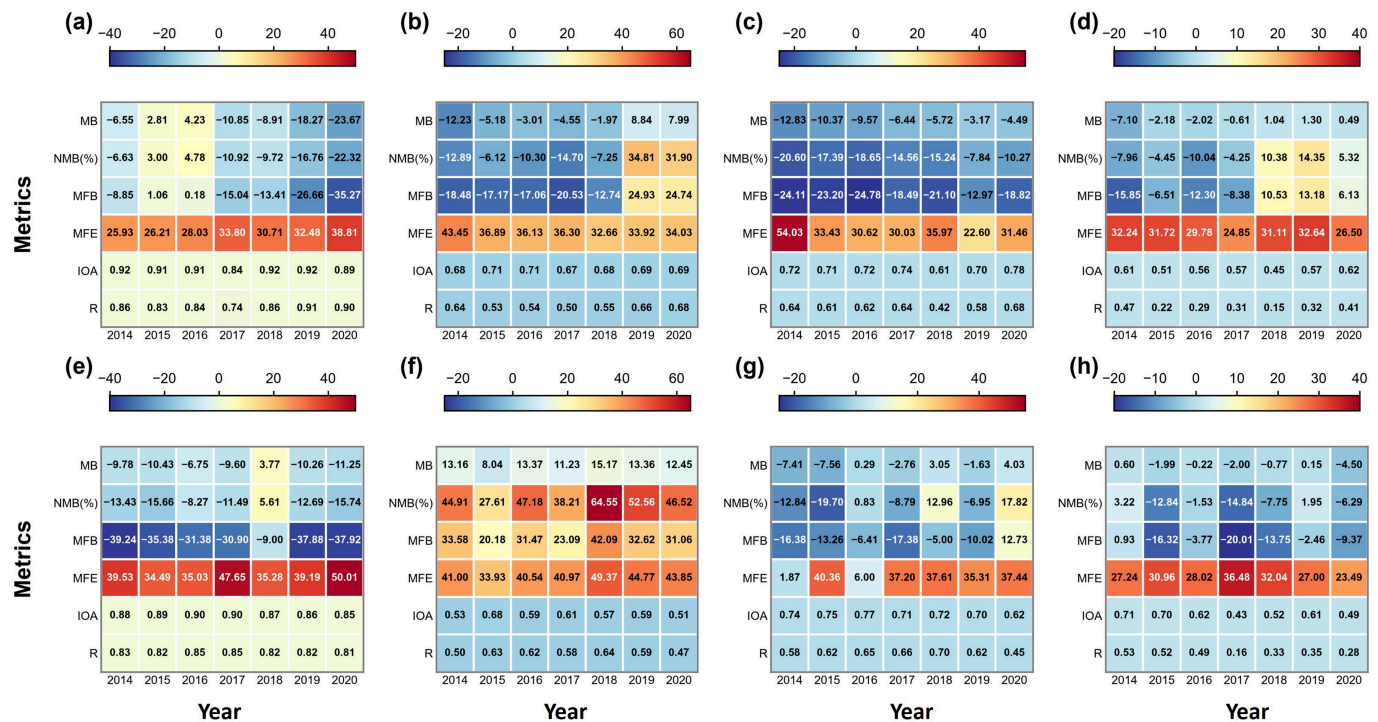


Figure 3. Model evaluation statistics for surface air pollutant concentrations in the Bohai Plain (a–d) and the YRD (e–h). (a) O₃ (μg/m³); (b) NO₂ (μg/m³); (c) PM_{2.5} (μg/m³); (d) SO₂ (μg/m³); (e) O₃ (μg/m³); (f) NO₂ (μg/m³); (g) PM_{2.5} (μg/m³); (h) SO₂ (μg/m³).

NO₂ exhibited clear regional contrasts. It was underestimated in most years over the Bohai Plain, with MB between negative 12.23 and 8.84 μg m^{−3}, whereas it was overestimated over the YRD, with MB between 8.04 and 15.17 μg m^{−3}. These differences may reflect spatial heterogeneity in industrial and traffic-related NO₂ emissions and local uncertainties in the emission inventory. For SO₂, simulated concentrations were slightly lower than observed values in most years, with MB between negative 7.10 and 1.39 μg m^{−3}, and met the Boylan and Russell [43] acceptability criteria of MFB between negative 60% and 60% and MFE less than or equal to 75%. For PM_{2.5}, MFB and MFE over the full study period ranged from negative 31.26% to 12.73% and from 6.00% to 40.36%, respectively, indicating acceptable performance. Except for 2020 in the YRD, PM_{2.5} IOA exceeded 0.70, further supporting satisfactory model skill.

It should be acknowledged that model biases may arise from limitations in WRF-Chem parameterizations, uncertainties in emission inventories, and errors in the initial and boundary conditions [47]. Nevertheless, combined surface and radiosonde evaluations using multiple metrics indicate that WRF-Chem reasonably reproduced the principal thermodynamic variability, surface pollutant concentrations and their spatiotemporal variations, and the general lower tropospheric profile structures in the two study regions. The magnitude of wind speed, particularly within the lowest 1 km, remained an important source of uncertainty and should therefore be considered when interpreting spatial features associated with atmospheric transport. Overall, the model performance provides an adequate foundation for attributing O₃ responses to anthropogenic emission changes and diagnosing regional differences in O₃ formation sensitivity.

3.2. Spatial and Temporal Evolution of Peak Summer Surface O₃ over Two Major Emission Hotspots in Eastern China

The Bohai Plain and the YRD are strongly influenced by multiple anthropogenic emission sectors. Their surface O₃ variability reflects the combined effects of emission changes,

meteorological conditions, photochemical processes, and regional transport, resulting in distinct spatial patterns and temporal evolution (Figure 4).

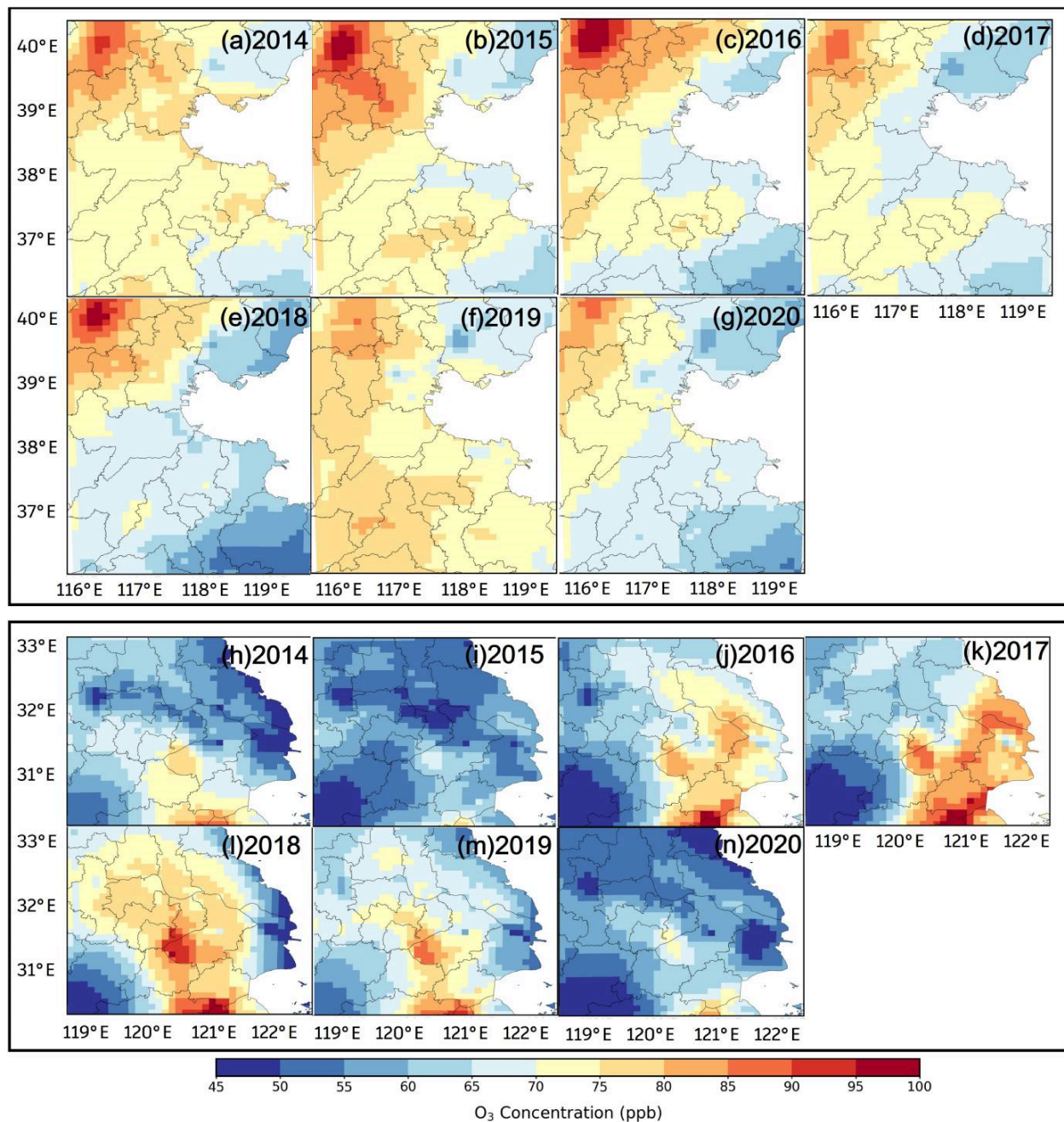


Figure 4. Spatial distribution of WRF-Chem simulated MDA8 O₃ in July. (a–g) 2014~2020 of Bohai Plain; (h–n) 2014~2020 YRD.

The two regions shared some broad temporal features, most notably relatively high July MDA8 O₃ levels by 2019 followed by marked decreases in 2020, although their year to year variations differed. Over the Bohai Plain, the July mean MDA8 O₃ increased from 73.42 ppb in 2014 to 74.11 ppb in 2019 and then dropped to 68.58 ppb in 2020, a 7.46% decrease relative to 2019 and below the 2014 level. The abrupt decline in 2020 was consistent with the combined influence of reduced anthropogenic activities and meteorological variability reported across eastern China during the COVID-19 period [48–51]. Changes in regional transport and background O₃ may have further contributed to the widespread decrease. By contrast, the gradual increase during 2014 to 2019 is consistent

with favorable meteorological conditions, including more clear sky days and more frequent hot and dry conditions, and with nonlinear O_3 responses to emission reductions [15]. In highly polluted urban areas, NO_x reductions can weaken O_3 titration and partly offset the benefits of precursor controls.

The YRD shows a more complex temporal pattern. The July mean MDA8 O_3 decreased from 58.82 ppb in 2014 to 55.41 ppb in 2015 and then increased to 65.19 ppb in 2016, remaining high during 2017 to 2019. In 2020, it decreased by 9.26 ppb relative to 2019, consistent with the abrupt decline over the Bohai Plain. The 2014 to 2019 increase was closely associated with an imbalance between NO_x and VOC reductions. Controls targeted NO_x sources from industry and transportation, whereas VOC controls lagged for sources such as industrial solvent use and coating production. Under predominantly VOC-limited or transitional conditions, stronger NO_x reductions relative to VOC reductions weakened NO titration and modified radical cycling, thereby favoring O_3 accumulation in urban and industrialized areas [52,53]. The sharp decline in 2020 likely also reflects broader-scale emission reductions during the pandemic, including decreases in free tropospheric O_3 and their influence on near-surface O_3 [50,54].

In terms of spatial patterns, the distributions and evolution of high O_3 areas show distinct regional characteristics. Over the Bohai Plain, O_3 generally exhibits higher concentrations in the west than in the east and in the north than in the south. Inland areas farther from the coast, such as central and southern Hebei, show higher concentrations than parts of the coastal zone. This contrast between inland and coastal areas likely reflects the combined influence of precursor distributions, local photochemical production, boundary layer development, regional transport, and coastal circulation. From 2014 to 2018, the high O_3 area, defined as MDA8 O_3 greater than 72 ppb, remained relatively stable and was mainly concentrated over Beijing, Tianjin, Hebei, and surrounding areas with intensive emissions. In 2019, the high O_3 area expanded rapidly, covering most of Hebei and northern Shandong, whereas it contracted across the entire domain in 2020, with the largest simulated decreases occurring over less urbanized portions of the domain. This spatial evolution reflects both regional differences in anthropogenic emissions and meteorological control of pollutant dispersion. Marine inflow and coastal circulation may either enhance ventilation or redistribute O_3 and its precursors, while dense precursor emissions and regional accumulation can favor elevated O_3 over inland areas. These patterns provide an initial indication of spatially heterogeneous O_3 changes across areas with different levels of urban development and offer a basis for further investigation.

Over the YRD, areas of elevated O_3 were concentrated in the central and southern parts of the region and alternately expanded northward and contracted. The core high O_3 area is located over northern Zhejiang, southern Jiangsu, and Shanghai, where dense urban, industrial, and transport emissions maintain high precursor levels and active photochemical production, forming a regional O_3 hotspot. From 2014 to 2018, the high O_3 area expanded gradually from south to north and extended to surrounding areas in central and northern Jiangsu and southeastern Anhui, indicating combined influences of regional transport and local emissions. The high O_3 area reached its largest extent in 2019 and then contracted rapidly southward in 2020, with the core high-value area shrinking by more than 50% and particularly large decreases over nonurban areas. This evolution reflects the combined effects of emission distributions, transport pathways, and regional meteorological conditions. The source strength of the central and southern core region dominated the formation of high O_3 , while north-south dispersion pathways modulated expansion and contraction. The widespread contraction in 2020 is consistent with the combined influence of anthropogenic emission reductions, meteorological variability, and regional transport on the spatial pattern.

Overall, the two regions exhibited distinct spatial structures and different amplitudes of interannual variation. The Bohai Plain showed a pronounced inland-to-coastal gradient, whereas the YRD maintained a persistent hotspot along its central urban and industrial corridor. Both regions reached relatively high O_3 levels by 2019 and declined markedly in 2020, but their year-to-year evolution differed, indicating that the baseline simulations reflected varying combinations of meteorology, emissions, and regional transport.

3.3. Regional Evolution of Peak Summer O_3 Formation Sensitivity

The H_2O_2 to HNO_3 ratio was used to diagnose O_3 formation sensitivity. This indicator represents competition between radical termination through HO_2 self-reactions, which favors H_2O_2 formation under relatively low NO_x conditions, and termination through the reaction of OH with NO_2 , which produces HNO_3 under NO_x -rich conditions. Higher ratios generally indicate greater sensitivity to NO_x , whereas lower ratios indicate greater sensitivity to VOCs [55,56]. Following previous modeling studies, grid cells with ratios above 0.65 were classified as sensitive to NO_x , those below 0.35 were classified as sensitive to VOCs, and those between 0.35 and 0.65 were classified as mixed sensitive [18,57]. This classification was applied consistently to characterize the spatial and temporal evolution of O_3 formation sensitivity in the two regions (Figure 5).

O_3 formation sensitivity over the Bohai Plain shows a clear west–east contrast and a shift in the dominant controlling factors. From 2014 to 2018, sensitivity was mainly characterized by mixed sensitivity and NO_x -sensitive regimes. In the central and eastern parts of the domain, the regime gradually shifted from mixed sensitivity toward NO_x sensitivity, suggesting that changes in the relative abundance of NO_x and VOCs favored stronger NO_x sensitivity in these areas. Meanwhile, VOC-sensitive areas over Beijing, Tianjin, and surrounding locations contracted and ultimately disappeared, consistent with changes in urban VOC-related controls and precursor conditions. A major transition occurred in 2019, when the sensitivity pattern reversed. The western inland area became entirely VOC-sensitive, the eastern part was dominated by mixed sensitivity, and NO_x -sensitive areas nearly vanished. In 2020, this pattern remained largely unchanged, except that parts of the VOC-sensitive regime in the southwest shifted toward mixed sensitivity. Overall, the sensitivity evolution corresponded closely to changes in the relative availability of NO_x and VOCs. During the earlier period, declining NO_x emissions accompanied by stable or slightly increasing VOC emissions reduced effective NO_x availability relative to VOCs, favoring mixed regimes and regimes with greater sensitivity to NO_x in parts of the region. After VOC emissions began to decline, changes in the precursor balance and regional photochemical processing were accompanied by a shift toward VOC-sensitive conditions over the western part of the domain in 2019–2020. The eastern part retained predominantly mixed sensitivity, indicating a more balanced influence of the two precursors.

O_3 formation sensitivity varied spatially across the YRD, with strengthening NO_x sensitivity in the north and transitions in dominant control regimes. In 2014, sensitivity was dominated by mixed sensitivity and NO_x sensitivity, while VOC-sensitive areas were confined to small locations near Suzhou and Wuxi and around the boundary between Zhenjiang and Yangzhou. Spatially, the southwest and the eastern periphery were mainly NO_x -sensitive, whereas the northern and central parts were largely mixed sensitivity, reflecting relatively high NO_x levels and more localized VOC influences. From 2014 to 2017, the pattern evolved gradually: NO_x -sensitive areas in the east shifted toward mixed sensitivity, and the VOC-sensitive regime expanded slightly without altering the overall distribution, consistent with strengthened NO_x controls and comparatively slower VOC controls. In 2018, the sensitivity pattern briefly returned to a distribution similar to that in 2014, suggesting that interannual changes in meteorology, transport, and precursor avail-

ability jointly modified regional photochemical conditions. During 2018 to 2020, sensitivity shifted more rapidly. Mixed sensitivity areas in the north and southwest transitioned to NO_x sensitivity, whereas parts of the NO_x -sensitive regime in the southeast shifted to mixed sensitivity. Notably, the VOC-sensitive regime disappeared and was replaced by mixed sensitivity. This transition indicates a substantial change in precursor emission structure. Sustained NO_x reductions increased the role of NO_x in regulating O_3 formation, whereas strengthened VOC controls reduced the dominance of VOC limitation. In the central and southern core areas, a more balanced NO_x -to-VOCs ratio supported a stable mixed sensitivity regime.

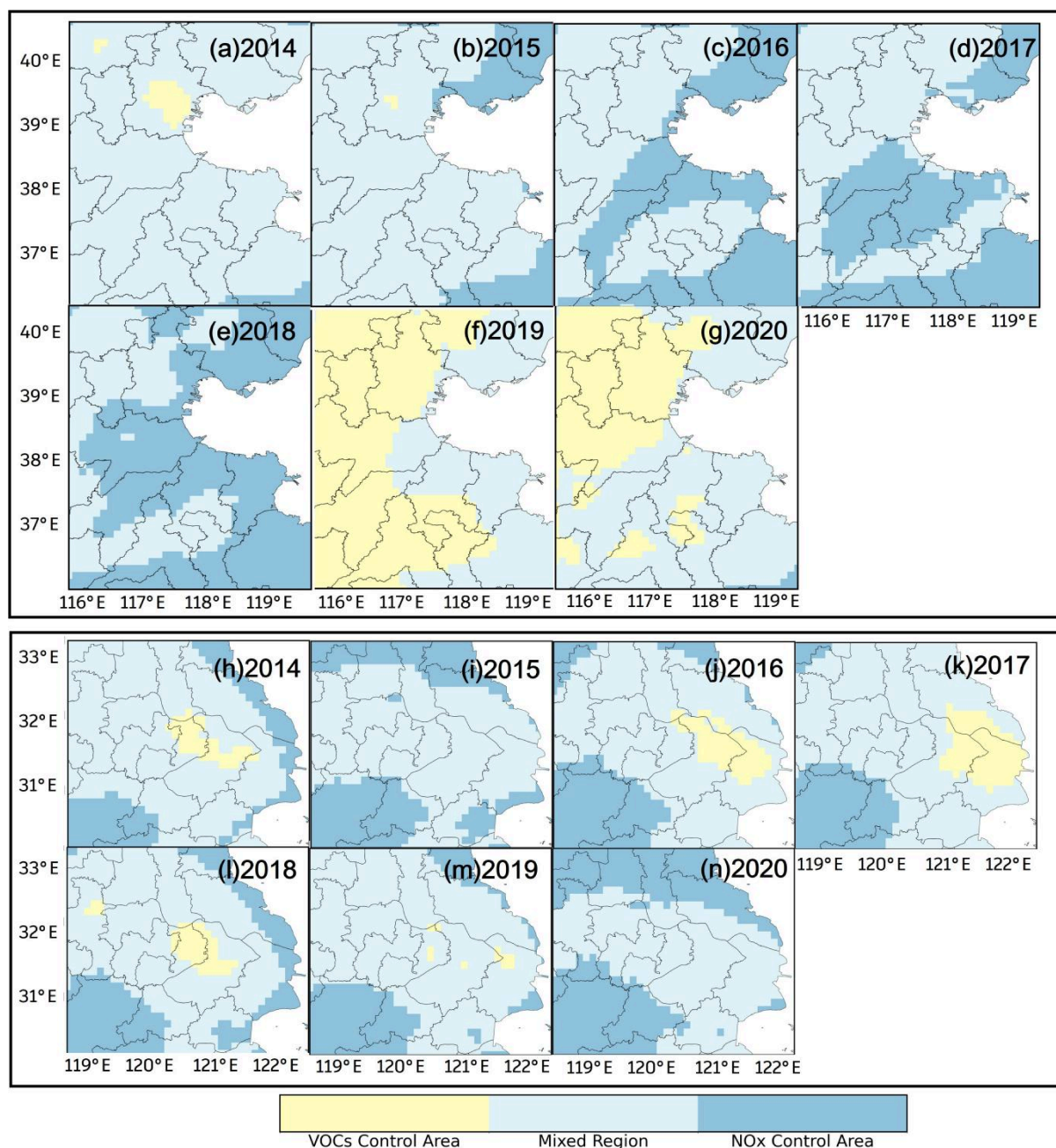


Figure 5. Trends in the spatial distribution of O_3 generation sensitivity in the Bohai Plain and YRD in July 2014–2020. (a–g) 2014–2020 of Bohai Plain; (h–n) 2014–2020 of YRD.

The contrasting evolution of O_3 sensitivity provides chemical context for the different emission responses in the two regions. Over the Bohai Plain, the expansion of areas sensitive

to VOCs increased the effectiveness of VOC reductions, particularly in the western domain. Over the YRD, widespread mixed sensitivity and the changing influence of NO_x created conditions under which reductions in NO_x without sufficient VOC control could increase O_3 . These patterns indicate that the same nominal reduction in a precursor can produce different outcomes when regional precursor balances and chemical environments differ.

3.4. Effects of Anthropogenic Emission Changes on Regional O_3

Using the total and individual pollutant emission substitution results, we examined how anthropogenic emission changes affected O_3 under fixed meteorological conditions and identified the major factors responsible for the regional differences (Figures 6–10).

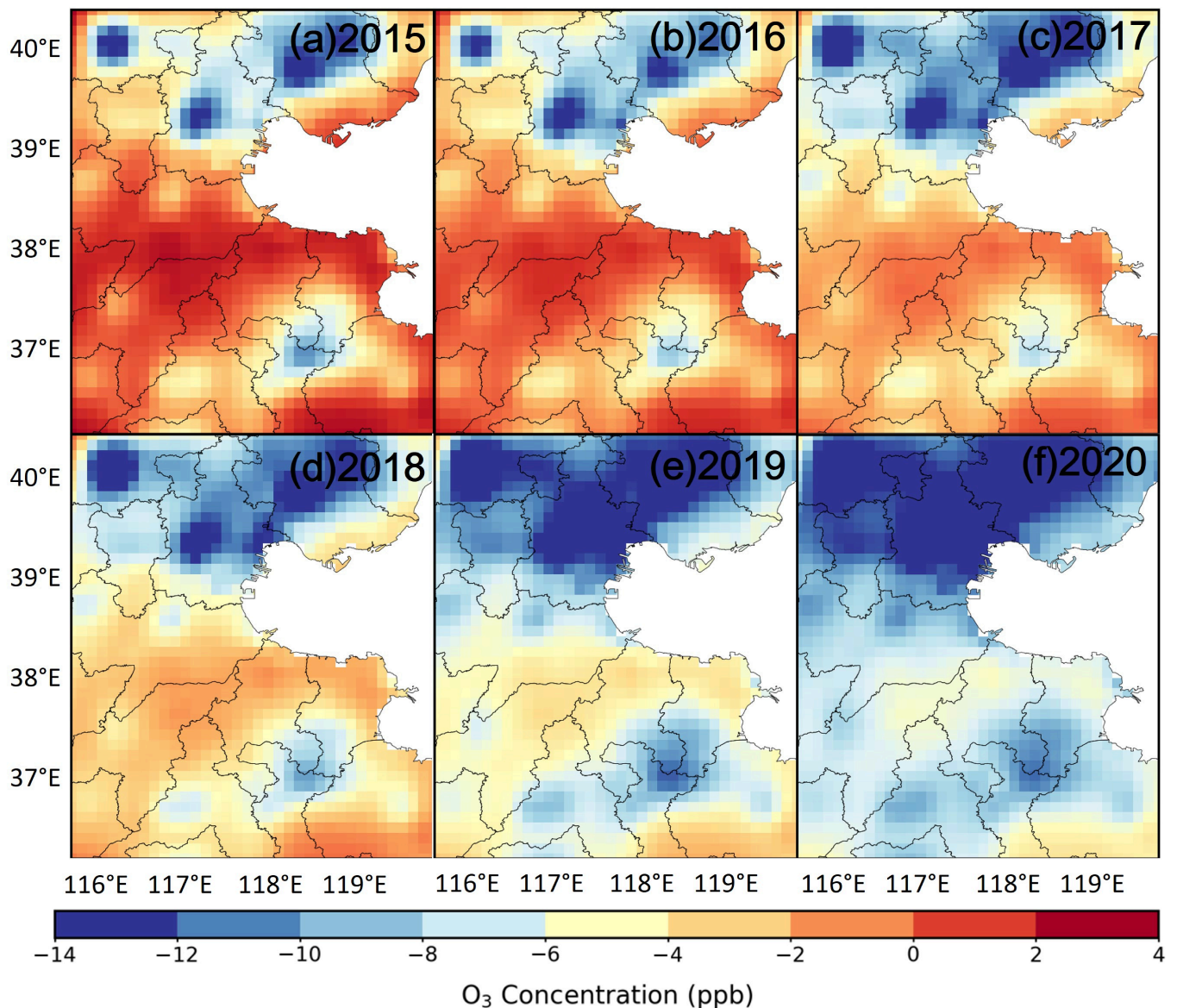


Figure 6. Differences in the change in monthly mean surface MDA8 O_3 concentrations in July, simulated for the Bohai Plain using S14AE15, S14AE16, S14AE17, S14AE18, S14AE19, and S14AE20, compared to the baseline scenario S14AE14. (a) S14AE15–S14AE14; (b) S14AE16–S14AE14; (c) S14AE17–S14AE14; (d) S14AE18–S14AE14; (e) S14AE19–S14AE14; (f) S14AE20–S14AE14.

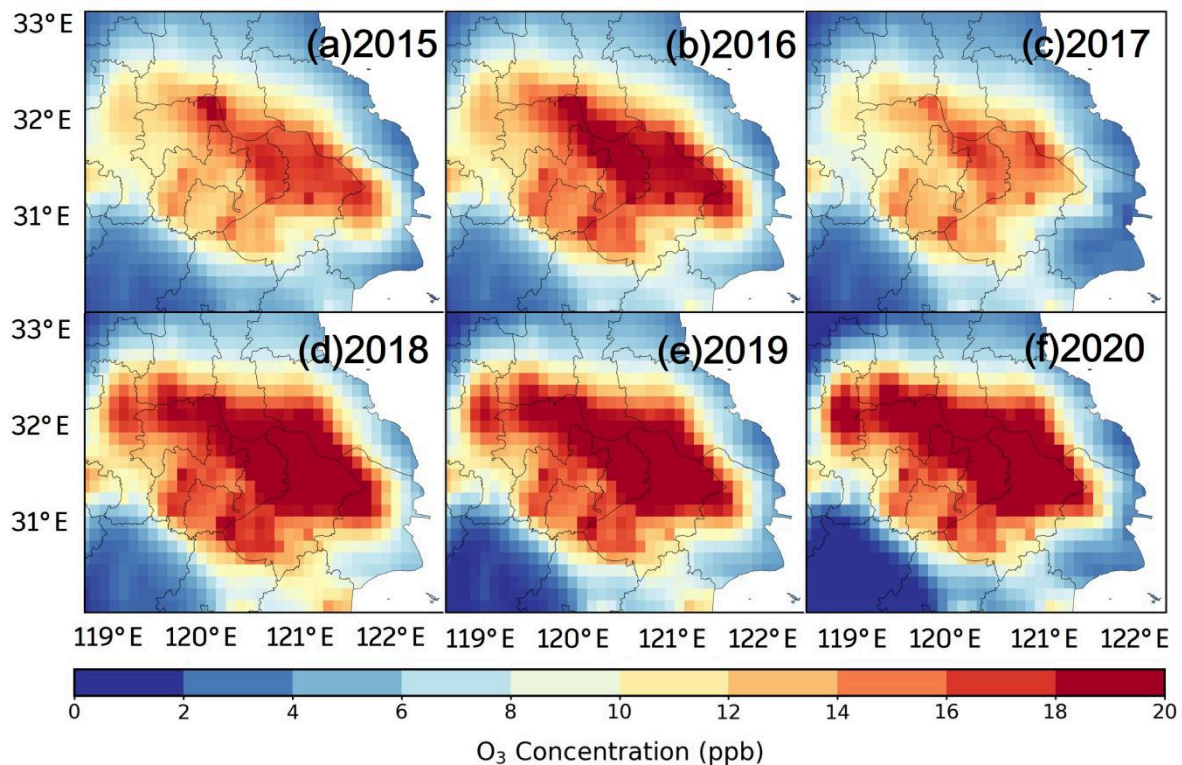


Figure 7. Differences in July surface MDA8 O₃ monthly mean concentration changes in the YRD, modeled by S14AE15, S14AE16, S14AE17, S14AE18, S14AE19, and S14AE20, compared to the baseline scenario S14AE14. (a) S14AE15–S14AE14; (b) S14AE16–S14AE14; (c) S14AE17–S14AE14; (d) S14AE18–S14AE14; (e) S14AE19–S14AE14; (f) S14AE20–S14AE14.

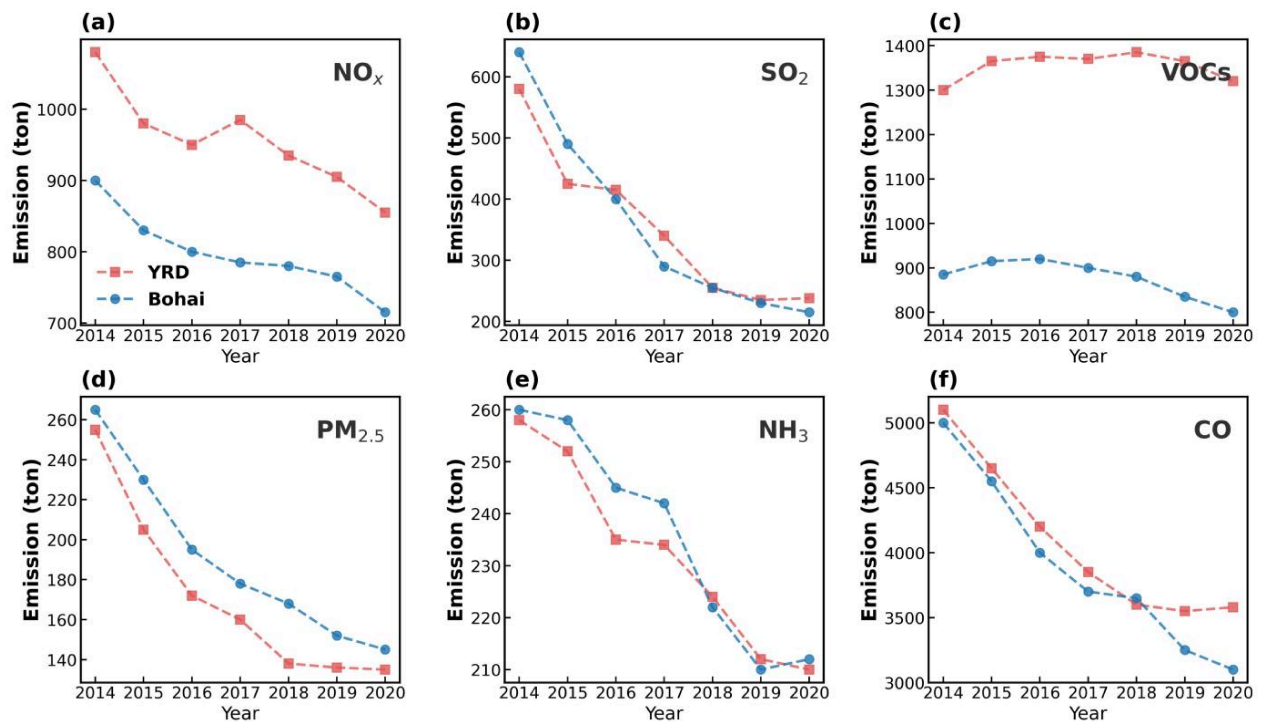


Figure 8. Trends in pollutant emissions from the MEIC in the Bohai Plain and YRD from 2014 to 2020. (a) NO_x; (b) SO₂; (c) VOCs; (d) PM_{2.5}; (e) NH₃; (f) CO.

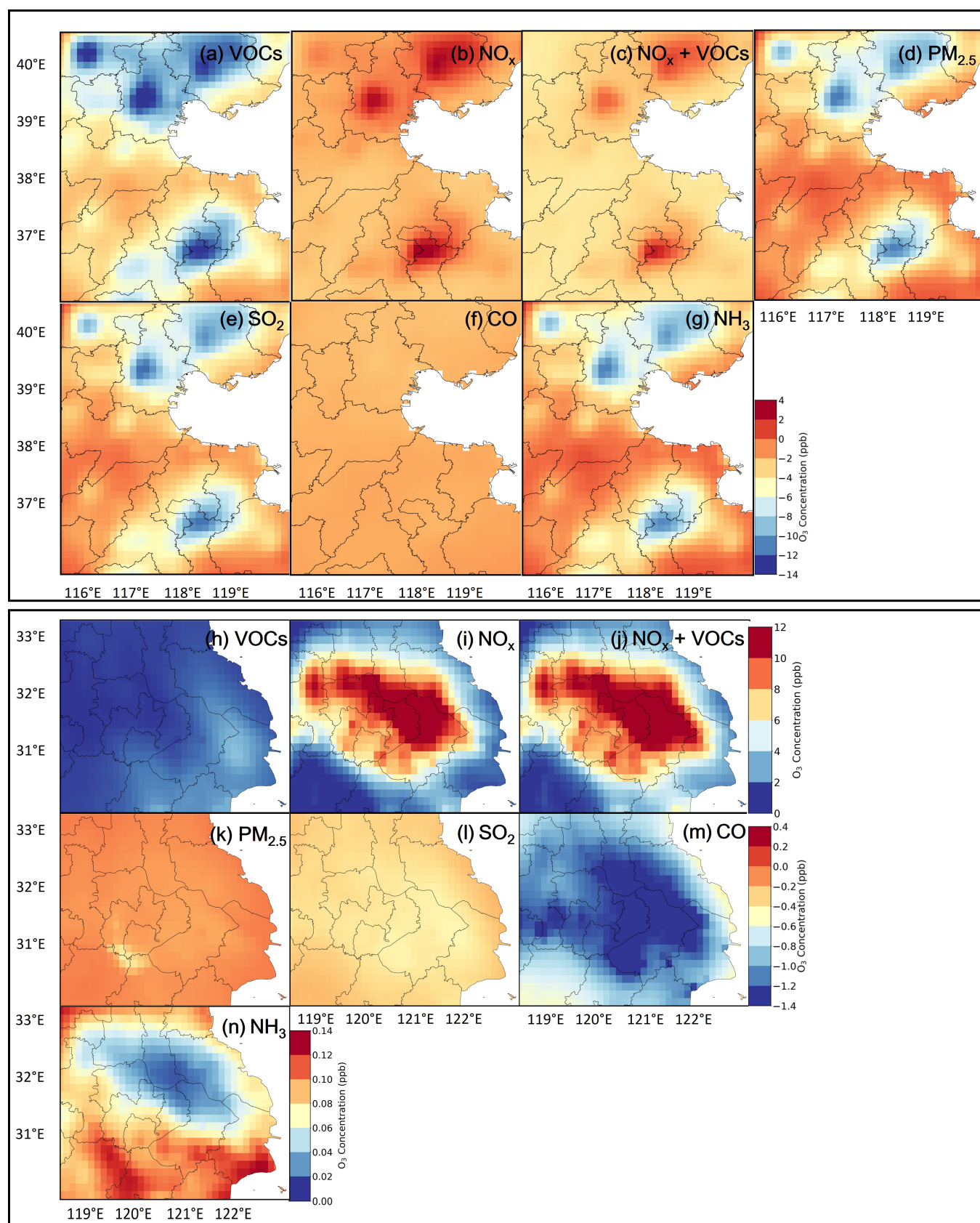


Figure 9. Response of July mean MDA8 O₃ to single pollutant substitution experiments in the Bohai Plain (a–g) and the YRD (h–n). In each single pollutant substitution experiment, emissions of the target pollutant were replaced by their 2020 values, while meteorology and all other pollutant

emissions were fixed at 2014 levels. Differences are relative to the 2014 baseline simulation, with positive values indicating O₃ increases and negative values indicating O₃ decreases. Panels (a–g) and (h–n) represent VOCs, NO_x, NO_x plus VOCs, PM_{2.5}, SO₂, CO, and NH₃ for the Bohai Plain and YRD, respectively.

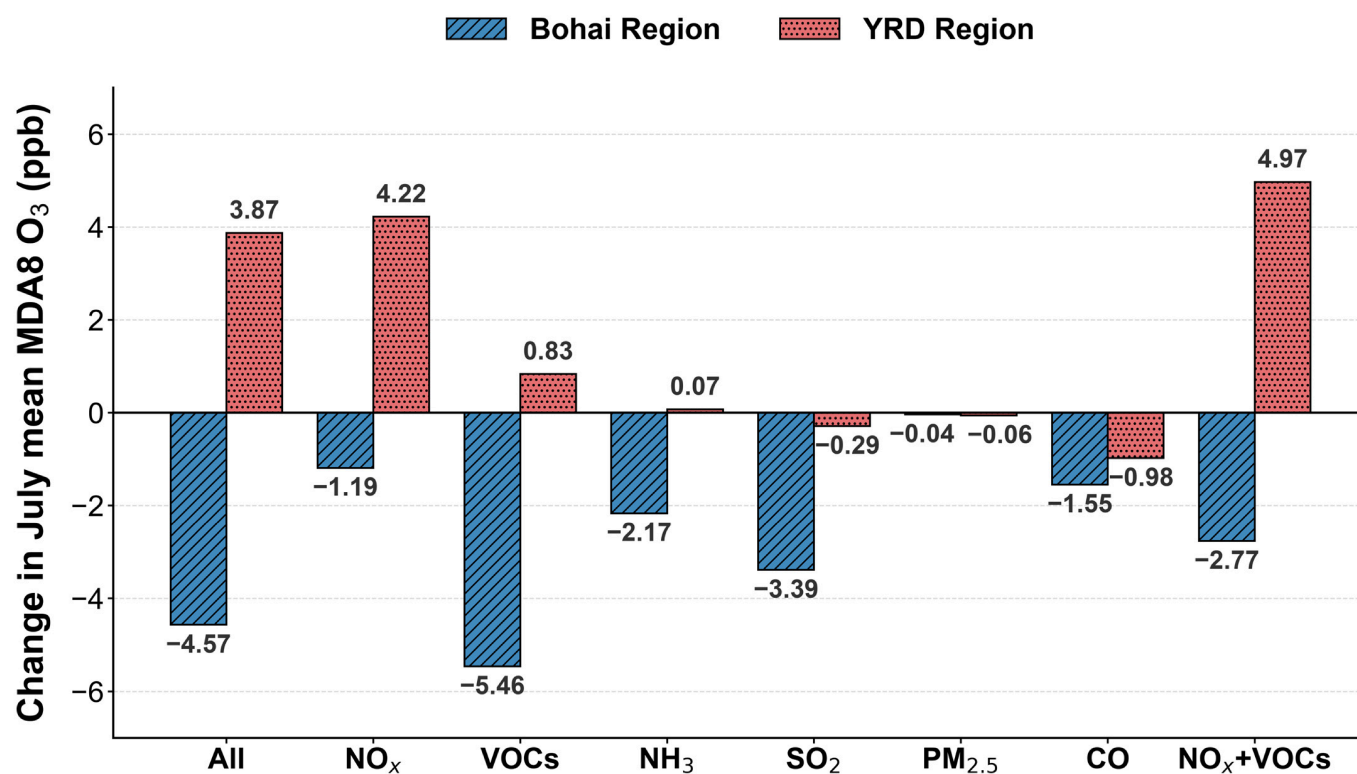


Figure 10. Regional mean changes in July MDA8 O₃ over the Bohai Plain and the YRD when 2014 total or individual pollutant emissions were replaced with those for 2020.

3.4.1. Contrasting Regional Responses to Total Anthropogenic Emission Changes

The direction of the O₃ response to changes in total anthropogenic emissions differed markedly between the two regions under fixed 2014 meteorological conditions, reflecting differences in emission structure, geographic setting, and photochemical processes.

Over the Bohai Plain, substituting each annual anthropogenic emission inventory after 2014 produced a negative regional mean O₃ response. Relative to S14AE14, MDA8 O₃ decreased by 0.98, 1.16, 2.11, 2.59, 3.79, and 4.57 ppb when the inventories for 2015 through 2020 were applied, respectively. The progressively larger decreases indicate that the evolving regional emission mixture became increasingly favorable for O₃ reduction. Spatially, the strongest decreases occurred over the northern urban agglomeration and the central and southern parts of the domain. Areas with weak positive responses under the earlier emission substitutions gradually contracted, and nearly the entire region exhibited a negative response when the 2020 inventory was applied (Figure 6).

The YRD exhibited the opposite response. Replacing the 2014 anthropogenic emission inventory with each subsequent annual inventory increased regional mean O₃. Relative to S14AE14, the O₃ responses were +3.40, +3.92, +3.13, +4.70, +4.18, and +3.88 ppb for the 2015, 2016, 2017, 2018, 2019, and 2020 emission inventories, respectively. Although response magnitude varied among the inventory years, it remained positive in all six experiments. The positive responses were concentrated along the central urban and industrial corridor and extended into surrounding areas. This pattern was associated with a substantial reduction in NO_x emissions without a comparable decrease in VOC emissions. Under VOC-sensitive and mixed-sensitive conditions, this imbalance weakened NO titration and

altered radical cycling, allowing O₃ to increase despite reductions in total anthropogenic emissions. The outward extension of the positive response also suggests a role for regional transport (Figure 7).

Together, the fixed meteorology results reveal the central regional contrast identified in this study. Changes in anthropogenic emissions consistently reduced regional mean O₃ over the Bohai Plain but consistently increased it over the YRD. This contrast was not directly apparent in the baseline simulations, which combined interannual variations in meteorology and emissions. Similar features in baseline O₃ evolution therefore do not necessarily indicate common anthropogenic drivers. Instead, the direction of the O₃ response depends on the evolution of the complete regional emission mixture and its interaction with the prevailing chemical regime, rather than simply on whether total emissions increase or decrease. July 2014 showed no marked anomalies in the four regional mean meteorological indicators relative to their 2014 to 2020 distributions (Figure A5), indicating that it did not provide an evidently extreme regional meteorological background for the controlled comparison. The fixed meteorology design provides a consistent basis for isolating and comparing the O₃ responses to prescribed emission changes under identical meteorological conditions. Nevertheless, because regional mean indicators cannot fully characterize interannual differences in circulation, the results should be interpreted as controlled emission responses under July 2014 conditions. The extent to which the regional contrast, response magnitude, and spatial expression vary under alternative meteorological years remains to be examined.

3.4.2. Responses to Changes in Individual Pollutant Emissions

The O₃ responses to changes in individual pollutant emissions differed markedly between the two regions, reflecting differences in emission trajectories and regional atmospheric chemistry. Under fixed 2014 meteorological conditions, the 2020 emissions of each target pollutant were substituted individually to quantify the corresponding change in regional mean O₃. Over the Bohai Plain, emissions of all selected pollutants were lower in 2020 than in 2014. SO₂ showed the largest decrease of 66.77%, followed by PM_{2.5}, CO, NO_x, and NH₃, which decreased by 46.04%, 38.08%, 20.22%, and 18.53%, respectively. VOC emissions increased slightly from 2014 to 2016 and subsequently declined, resulting in a net decrease of 9.62% by 2020. Over the YRD, VOC emissions increased slightly by 1.31%, whereas NO_x, CO, NH₃, PM_{2.5}, and SO₂ emissions declined. The 20.95% reduction in NO_x represented the most important change in the regional precursor emission structure (Figure 8).

Over the Bohai Plain, the individual pollutant substitutions generally decreased regional mean O₃, although the magnitude and spatial pattern varied considerably among pollutants (Figures 9 and 10). VOC substitution produced the largest decrease of 5.46 ppb, with the strongest negative responses over Beijing, Tianjin, and parts of Hebei. These areas contain dense industrial and urban VOC sources, and their response is consistent with VOC controls suppressing photochemical O₃ production [58]. The SO₂ and NH₃ substitutions decreased regional mean O₃ by 3.39 ppb and 2.17 ppb, respectively. Both produced negative responses over urban areas but weak positive responses over parts of the central and southern rural areas. Because SO₂ and NH₃ influence secondary aerosol formation, their spatially heterogeneous effects may reflect changes in photolysis, aerosol surface area, heterogeneous radical loss, and atmospheric oxidation capacity [15,59]. The NO_x, CO, and PM_{2.5} substitutions produced smaller regional mean decreases of 1.19 ppb, 1.55 ppb, and 0.04 ppb, respectively. The NO_x response differed between urban and rural areas. Lower NO_x increased O₃ in urban centers by weakening titration and altering radical termination under VOC-sensitive conditions, whereas it suppressed O₃ production in sur-

rounding areas with lower NO_x availability. The negative response to the CO substitution is consistent with reduced HO_2 production and weaker radical propagation following lower CO emissions [12,60]. When the 2020 NO_x and VOC emissions were substituted simultaneously, regional mean O_3 decreased by 2.77 ppb. This decrease was smaller than that produced by the VOC substitution alone and substantially smaller than the sum of the separate responses, indicating that the NO_x change offset part of the O_3 reduction associated with declining VOC emissions.

The YRD exhibited a fundamentally different response. Substituting the 2020 NO_x emissions increased regional mean O_3 by 4.22 ppb, with the strongest increases along the central urban and industrial corridor. This response is consistent with substantial VOC sensitivity in the core area, where declining NO_x weakens titration and modifies radical termination, allowing O_3 to accumulate. The slight increase in VOC emissions produced an additional O_3 increase of 0.83 ppb. Simultaneous substitution of NO_x and VOC emissions increased regional mean O_3 by 4.97 ppb, exceeding either individual response but remaining slightly below their arithmetic sum. This result further demonstrates that O_3 responses to concurrent precursor changes are not strictly additive. In contrast, the CO substitution decreased regional mean O_3 by 0.98 ppb and therefore partly offset the increase associated with changes in NO_x and VOC emissions. The NH_3 substitution produced only a small increase of 0.07 ppb, while the SO_2 and $\text{PM}_{2.5}$ substitutions decreased O_3 by 0.29 ppb and 0.06 ppb, respectively. These comparatively small responses indicate that regional mean O_3 changes over the YRD were governed primarily by the evolving NO_x and VOC balance, with a secondary influence from CO.

Overall, the contrasting responses were determined by the interaction between regional emission trajectories and O_3 formation sensitivity. Over the Bohai Plain, declining VOC emissions produced the strongest direct suppression of O_3 , while changes in SO_2 and NH_3 generated additional spatial variability through interactions between aerosol processes and photochemistry. Over the YRD, substantial NO_x reductions increased O_3 , the slight rise in VOC emissions reinforced this response, and declining CO emissions provided a partial offset. The strongly nonadditive responses to combined NO_x and VOC changes further show that the effects of individual pollutant controls cannot be interpreted as independent contributions. Effective O_3 mitigation should therefore coordinate NO_x , VOC, and CO controls according to regional chemical conditions rather than applying uniform emission reduction priorities across both regions.

4. Discussion

This study focused on the Bohai Plain and the YRD, two representative regions, and used WRF-Chem with a controlled variable approach to investigate how anthropogenic emission changes affected July near-surface O_3 during 2014 to 2020 and to characterize the spatiotemporal differentiation of O_3 formation sensitivity. The results corroborate established understanding of nonlinear O_3 chemistry while revealing substantial regional contrasts in the direction and magnitude of emission-driven O_3 responses, providing a comparative basis for differentiated peak-summer mitigation.

4.1. Contrasting Anthropogenic Drivers of Regional O_3 Evolution

The most important regional contrast identified in this study is that anthropogenic emission changes produced persistently negative O_3 responses over the Bohai Plain but positive responses over the YRD under fixed meteorological conditions. This difference was not directly evident from the baseline simulations because the effects of meteorological variability and emission changes were superimposed. The positive response over the YRD is broadly consistent with previous studies showing that O_3 increased when NO_x

emissions declined without sufficiently strong VOC reductions [8,15,61,62]. Zhu et al. [21] further associated the O₃ increases over the North China Plain and YRD during 2016 to 2019 with shifts in formation regimes and enhanced atmospheric oxidation capacity. The progressively negative response over the Bohai Plain, however, indicates that this earlier relationship did not persist uniformly across regions and control stages. Recent national assessments have similarly shown that sustained emission reductions increasingly restrained O₃ after 2017, although the timing and magnitude of this transition varied regionally [63,64]. The present comparison further demonstrates that this transition could occur over the Bohai Plain while the YRD retained a positive emission-driven response.

The regional divergence was closely related to differences in the composition of emission changes. Over the Bohai Plain, VOC emissions declined together with NO_x, CO, SO₂, NH₃, and primary particulate matter. The reduction in VOC emissions weakened peroxy radical production, while changes in the other pollutants modified radical propagation, aerosol chemistry, and photolysis. Their combined effect produced an increasingly negative regional O₃ response. Over the YRD, the substantial decrease in NO_x was not accompanied by a comparable decline in VOC emissions. Under VOC-sensitive and mixed-sensitive conditions, this imbalance weakened O₃ titration by NO and reduced radical termination through the OH + NO₂ reaction, allowing O₃ to increase. Changes in particulate nitrate and aerosol loading may have further modified photolysis and HO₂ availability [8,15,65,66]. These results show that the O₃ response was governed by changes in the complete emission mixture and its interaction with the regional chemical regime, rather than by the total magnitude of emission reductions alone.

Beyond the regional mean responses, the July mean wind fields from the 2014 base simulation (S14AE14) illustrate potential regional transport pathways that may influence the spatial distribution of O₃ and its response to emission changes. Over the Bohai Plain, southerly and southeasterly winds indicated potential pathways for the northward transport of O₃ and its precursors from southern and coastal upwind areas (Figure A6a). Over the YRD, easterly and southeasterly winds prevailed across much of the region, indicating marine inflow and westward or northwestward transport, while southerly flow in the southern part provided an additional pathway from adjacent areas (Figure A6b). These circulation features suggest that regional transport can redistribute O₃ and its precursors and may therefore affect the spatial pattern of the simulated O₃ responses. Over the Bohai Plain, relatively high O₃ levels in the western and inland areas coincided with dense precursor emissions and regional pollutant accumulation, whereas lower values occurred along parts of the eastern coast. Previous studies have shown that both local formation and regional transport contribute substantially to summertime O₃ over the North China Plain [67,68]. In coastal areas, marine inflow and sea- and land-breeze circulations can alter pollutant transport and atmospheric residence time. Marine air may promote ventilation under some conditions, whereas recirculation between land and sea can return O₃ and its precursors to coastal areas and prolong O₃ pollution [69]. The influence of coastal circulation can therefore vary with the background flow, circulation intensity, and time of day.

Boundary layer structure further modulates the spatial distribution of surface O₃. Mixing layer depth affects the volume available for atmospheric mixing and regulates exchange between the surface layer, the residual layer, and the atmosphere above the boundary layer. Observations at multiple sites over the North China Plain have revealed pronounced differences in mixing layer development between inland and coastal areas. At Qinhuangdao, a coastal site on Bohai Bay, frequent sea breezes and the formation of a thermal internal boundary layer were associated with relatively low mixing layer heights in summer [70]. The importance of exchange between atmospheric layers is supported by O₃ process analysis over the North China Plain, which showed that transport from the

residual layer and above the boundary layer can substantially influence surface O_3 [71], and by observations showing that vertical turbulent heat flux, low-level jets, and wind shear can regulate exchange between atmospheric layers and near-surface pollutant concentrations [72]. Moreover, the response of MDA8 O_3 to mixing layer height can be nonlinear, indicating that boundary layer depth influences surface O_3 through interacting physical and chemical processes rather than through dilution alone [73]. Cloud cover, precipitation, and solar radiation can also regulate photochemical production and boundary layer development. Strong solar radiation favors photolysis and O_3 formation, whereas increased cloud cover and precipitation are generally associated with weaker solar radiation and changes in precursor and aerosol burdens. During a summertime O_3 pollution event on the North China Plain, weak solar radiation and low temperature suppressed photochemical O_3 production, while subsequent precipitation was accompanied by a reduction in O_3 pollution [68]. The spatial contrast across the Bohai Plain may therefore arise from the combined effects of precursor availability, local photochemistry, horizontal transport, vertical exchange, boundary layer development, and coastal circulation.

Over the YRD, the high O_3 area was concentrated along the urban and industrial corridor encompassing Shanghai and neighboring parts of Jiangsu and Zhejiang, where O_3 is jointly influenced by local emissions, transport from adjacent cities, and the regional background [74,75].

4.2. Changes in O_3 Formation Sensitivity and Implications for Regional Control

The regional divergence in O_3 responses was consistent with the simulated evolution of O_3 formation sensitivity. Over the Bohai Plain, the dominant pattern shifted from mixed regimes and conditions with greater NO_x sensitivity toward mixed-sensitive and VOC-sensitive conditions. During the earlier period, declining NO_x emissions accompanied by stable or slightly increasing VOC emissions moved parts of the region toward greater NO_x sensitivity. After VOC emissions began to decline, the changing precursor balance was accompanied by an expansion of VOC-sensitive conditions over the western domain. Over the YRD, the initial distribution consisted primarily of mixed-sensitive and NO_x -sensitive conditions, together with localized VOC-sensitive urban cores. Sustained NO_x reductions subsequently strengthened NO_x sensitivity in the north, while changes in both NO_x and VOC emissions supported mixed-sensitive conditions over the central region. These spatially heterogeneous changes are consistent with previous assessments of O_3 sensitivity across eastern China and with the reported transition of the Yangtze River corridor from predominantly VOC-sensitive toward mixed-sensitive chemistry [20,21,58,61].

These changes indicate that precursor control priorities should evolve with the regional chemical regime. Effective reductions in reactive VOC emissions remain particularly important in the western Bohai Plain, whereas coordinated NO_x and VOC reductions are more appropriate for the eastern domain. In the northern YRD, continued NO_x reductions are expected to become increasingly effective as the region moves toward greater NO_x sensitivity, but sufficient VOC control remains necessary in areas that retain VOC-sensitive chemistry. Coordinated reductions in both precursors are also required over the central and southern YRD, where mixed-sensitive conditions remain widespread. Regional strategies should therefore be adjusted according to changes in chemical sensitivity rather than remain fixed throughout the emission control period [15,61,63,66].

4.3. Chemical Interpretation of Individual Pollutant Responses

The individual pollutant substitutions identify different chemical pathways behind the regional responses. Over the Bohai Plain, substitution of the 2020 VOC emissions produced the largest regional mean O_3 decrease of 5.46 ppb. VOC oxidation generates organic peroxy

radicals that convert NO to NO₂ and support photochemical O₃ production. The strong negative response therefore indicates that declining VOC emissions substantially weakened radical propagation and O₃ formation [12,60,65]. The NO_x substitution produced a smaller regional mean decrease but opposite responses between urban and surrounding areas. In NO_x-rich and VOC-sensitive urban environments, lower NO_x weakens O₃ titration and radical termination, whereas in surrounding areas with lower NO_x availability, it suppresses reactions between peroxy radicals and NO and consequently reduces O₃ production [15,66,76].

Over the YRD, substitution of the 2020 NO_x emissions increased regional mean O₃ by 4.22 ppb, making NO_x the dominant individual driver of the positive response. The increase was strongest along the central urban and industrial corridor, where VOC-sensitive and mixed-sensitive conditions remained important. The slight increase in VOC emissions increased O₃ by 0.83 ppb, while simultaneous substitution of NO_x and VOC emissions increased O₃ by 4.97 ppb. This result demonstrates that the two precursors interacted through nonlinear photochemistry rather than acting independently. By contrast, CO reductions decreased O₃ by 1.55 ppb over the Bohai Plain and 0.98 ppb over the YRD. Because CO oxidation contributes to HO₂ production and subsequent NO-to-NO₂ conversion, lower CO emissions can shorten radical propagation chains and weaken photochemical O₃ production [12,60,65].

The responses to SO₂, NH₃, and primary particles mainly reflected their indirect influences on aerosol formation and multiphase chemistry. Changes in SO₂ and NH₃ emissions alter sulfate and nitrate aerosol formation, aerosol surface area, liquid water content, and radiative extinction. These properties affect photolysis and the heterogeneous uptake of HO₂, NO₂, and other reactive species, with the net O₃ response depending on aerosol composition, NO_x abundance, and the prevailing chemical regime [8,15,65,66]. This balance likely explains the spatially heterogeneous SO₂ and NH₃ responses over the Bohai Plain and their much smaller regional mean effects over the YRD. The near-zero response to primary PM_{2.5} substitution in both regions further indicates that changes in primary particle emissions made only a minor contribution to the regional mean O₃ response.

4.4. Study Limitations and Future Directions

July represents a high photochemical period in eastern China and provides a consistent basis for comparing regional O₃ responses under active photochemistry [10,19]. Nevertheless, a single month cannot capture the full variability of the O₃ season from May to September. Seasonal changes in temperature, solar radiation, precipitation, boundary layer development, synoptic circulation, and biogenic emissions may alter O₃ formation and affect the magnitude and spatial distribution of its responses to emission changes. Extending the analysis to other warm season months would help determine whether the regional differences identified in July persist across the broader O₃ season. Repeating the emission substitution experiments using meteorological conditions from additional representative years would also provide further insight into the influence of regional circulation and weather conditions on response magnitude.

MEIC provides a consistent multipollutant emission framework for both regions, although uncertainties remain in emission magnitude, temporal variation, chemical speciation, and spatial allocation. These uncertainties are particularly relevant for VOCs, NH₃, primary particulate matter, and soil-related emissions. Moreover, the 10 km model resolution may smooth fine-scale intraurban heterogeneity, as multiscale analysis of urban land data has shown that spatial aggregation can obscure local patterns and alter the apparent importance of their driving factors [77]. Future research combining higher-resolution inventories with satellite retrievals, surface observations, and detailed diagnostics of radicals

and aerosol processes would provide further evidence for the mechanisms inferred from the substitution experiments.

5. Conclusions

This study reveals that peak summer O₃ evolution across two major emission hotspots in eastern China can conceal fundamentally different anthropogenic drivers. Although the Bohai Plain and the YRD shared some broad temporal features, including relatively high O₃ levels by 2019 and marked declines in 2020, the experiments with constant meteorology showed opposite responses to annual anthropogenic emission changes. Over the Bohai Plain, substitution of each post-2014 emission inventory lowered regional mean MDA8 O₃ relative to S14AE14. The decreases were 0.98 ppb with the 2015 inventory and 4.57 ppb with the 2020 inventory. The comparison demonstrates that shared features in baseline O₃ evolution do not necessarily indicate common anthropogenic drivers.

The regional divergence was associated with differences in emission composition and chemical sensitivity. Over the Bohai Plain, a 9.62% reduction in VOC emissions produced the strongest negative O₃ response of 5.46 ppb and contributed to the progressively negative response of the complete emission mixture. Over the YRD, a 20.95% reduction in NO_x emissions increased O₃ by 4.22 ppb, while the slight increase in VOC emissions produced an additional positive response, and the reduction in CO partly offset this increase. The difference between the complete emission response and the separate substitution responses further indicates chemical interactions among precursor availability, radical cycling, titration, and aerosol processes. At the same time, the spatial expression of these regional responses may also be modulated by precursor distributions, local photochemistry, regional transport, boundary layer development, and coastal circulation.

Effective peak summer O₃ mitigation should therefore be based on regional emission composition and chemical sensitivity rather than on uniform reduction targets. Strong VOC control remains important over the Bohai Plain and should be coordinated with continued NO_x management. Over the YRD, further reductions in NO_x need to be accompanied by sufficiently effective VOC control to avoid adverse O₃ responses. More broadly, coordinated management of emissions from industrial, power, transport, residential, and agricultural sources across urban and surrounding nonurban environments is required to achieve consistent regional O₃ benefits. Extending this framework to other warm season months and additional representative meteorological years would further clarify the seasonal robustness and meteorological dependence of the regional differences identified here.

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Data Availability Statement: The publicly available ERA5 reanalysis data used in this study can be obtained from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels> (accessed on 1 September 2026)). The NCEP GDAS/FNL meteorological data are available from the NCAR Research Data Archive (<https://rda.ucar.edu/datasets/d083003/> (accessed on 1 September 2026)), and the CAM-Chem data used to generate the chemical initial and boundary conditions are available from NCAR ACOM (<https://www.acom.ucar.edu/cam-chem/cam-chem.shtml> (accessed on 1 September 2026)). The MEIC emission inventories and surface air-quality observations are available from the respective data providers (<http://meicmodel.org.cn/>

(accessed on 1 September 2026) and <https://air.cnemc.cn:18007/> (accessed on 1 September 2026)), subject to their access and use conditions. The Integrated Global Radiosonde Archive Version 2 data are available from NOAA National Centers for Environmental Information (<https://doi.org/10.7289/V5X63K0Q> (accessed on 6 September 2026)). The ChinaHighO3 dataset is available from Zenodo (<https://doi.org/10.5281/zenodo.21811088> (accessed on 6 September 2026)). The China Land Cover Dataset (CLCD) used to characterize the monitoring-station environments is publicly available from Zenodo (<https://doi.org/10.5281/zenodo.4417810> (accessed on 6 September 2026)). The processed data and WRF-Chem outputs supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. CNEMC monitoring stations used for O₃ model evaluation and their surrounding land-cover contexts.

Region	Station ID	Longitude (°E)	Latitude (°N)	Impervious Surface Within 2 km (%)
Bohai Plain	1017A	117.2370	39.1082	97.3
Bohai Plain	1019A	117.1837	39.2133	85.9
Bohai Plain	1037A	118.1310	39.6363	92.7
Bohai Plain	1040A	118.1705	39.6506	96.2
Bohai Plain	1046A	119.5251	39.9041	80.7
Bohai Plain	1067A	116.6708	39.5111	77.7
Bohai Plain	1072A	116.8584	38.3254	83.7
Bohai Plain	1300A	116.9376	36.6650	96.1
Bohai Plain	1303A	117.0624	36.6868	99.0
Bohai Plain	1625A	115.9848	36.4372	83.1
Bohai Plain	1630A	117.9776	37.3930	49.9
Bohai Plain	1632A	118.0253	36.8406	86.2
Bohai Plain	1648A	119.1200	36.7019	98.0
Bohai Plain	1656A	117.1437	36.1937	95.6
Bohai Plain	1666A	118.6614	37.4309	84.7
YRD	1146A	120.9780	31.0935	7.5
YRD	1160A	120.5610	31.2472	47.0
YRD	1169A	120.8600	32.0005	95.0
YRD	1171A	120.9400	31.9300	59.2
YRD	1184A	119.4600	32.3878	92.5
YRD	1189A	120.2750	31.6219	84.4
YRD	1196A	119.9633	31.7620	96.3
YRD	1199A	120.0393	31.7638	50.1
YRD	1206A	119.9050	32.4878	88.9
YRD	1231A	120.3019	30.4183	83.5
YRD	1249A	120.1000	30.8867	66.7
YRD	1252A	120.7436	30.7780	85.3
YRD	1993A	120.5260	31.8740	90.2
YRD	1995A	121.1150	31.4530	89.6
YRD	1999A	120.2680	31.9200	80.4
YRD	2002A	119.8180	31.3540	79.3
YRD	2004A	119.5790	31.7510	82.3
YRD	2006A	119.4600	31.4000	33.1
YRD	2008A	121.1730	31.8960	82.3

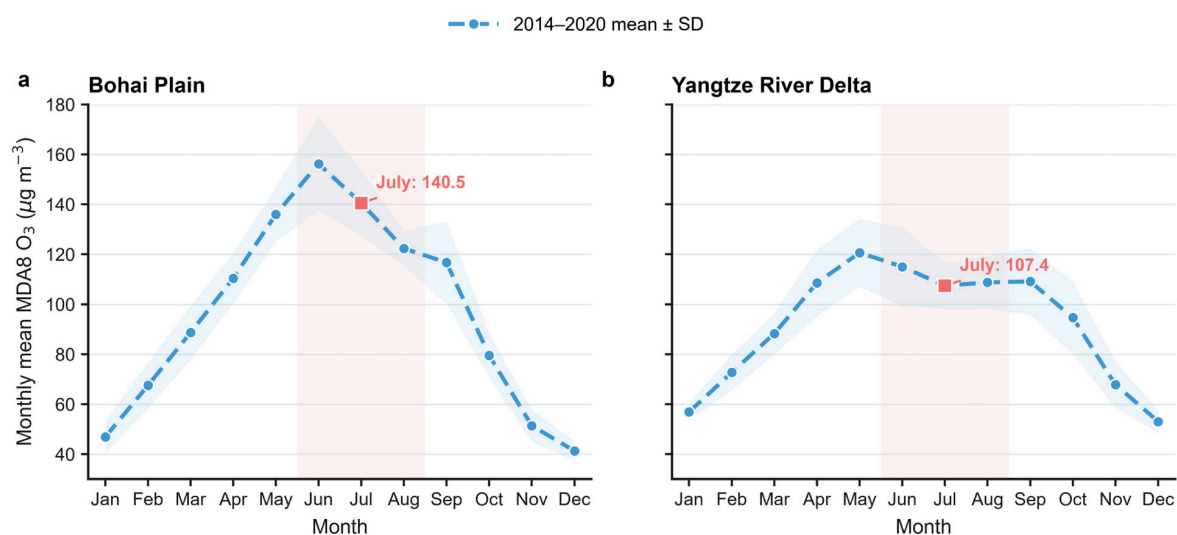


Figure A1. Annual cycles of monthly mean MDA8 O₃ concentrations over (a) the Bohai Plain and (b) the YRD during 2014–2020. The blue shaded bands indicate ± 1 standard deviation around the 2014–2020 mean for each month, whereas the pale red shading highlights the summer period from June to August.

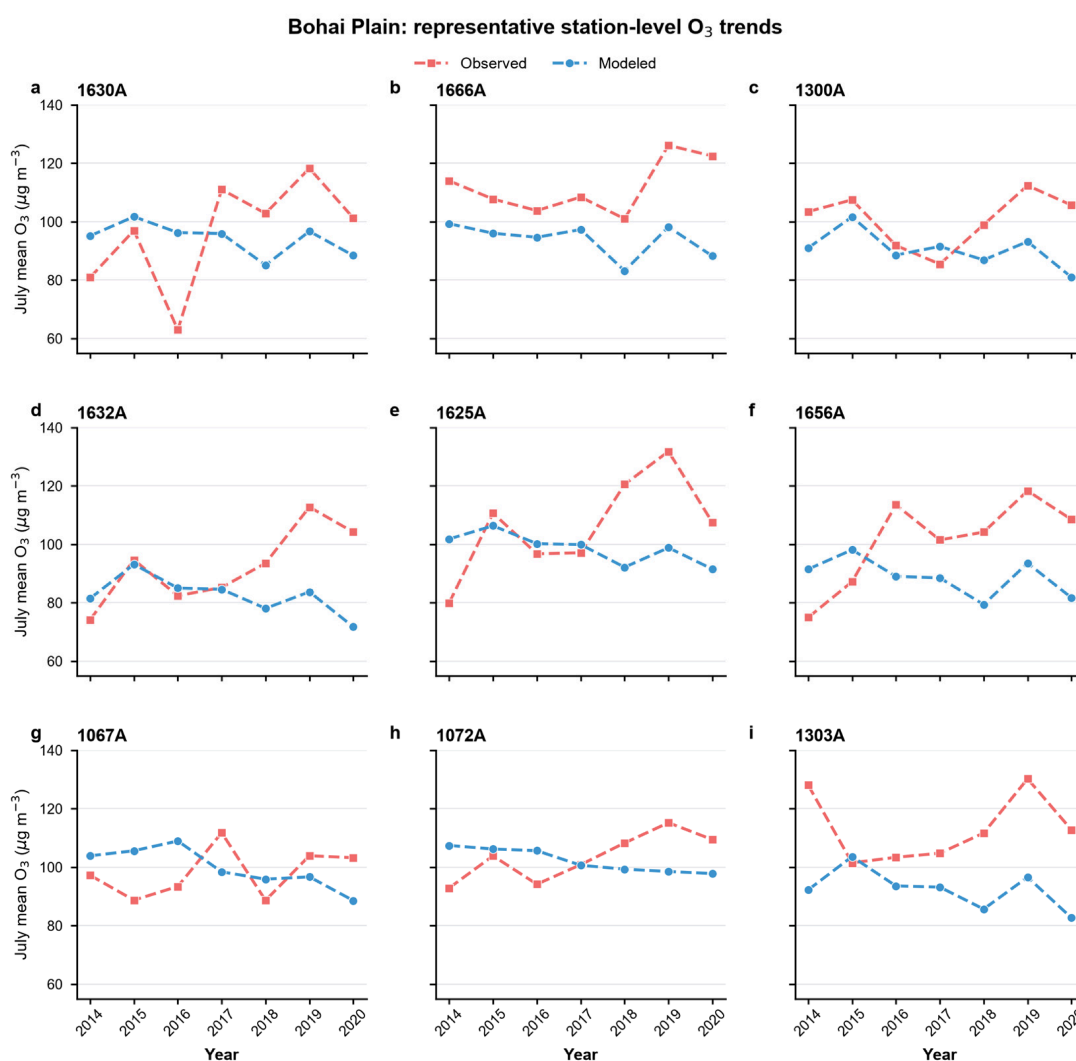


Figure A2. Interannual variations in observed and modeled July mean O₃ concentrations at representative monitoring stations over the Bohai Plain during 2014–2020. (a) 1630A; (b) 1666A; (c) 1300A;

(d) 1632A; (e) 1625A; (f) 1656A; (g) 1067A; (h) 1072A; (i) 1303A. Red squares and blue circles represent observations and model simulations, respectively.

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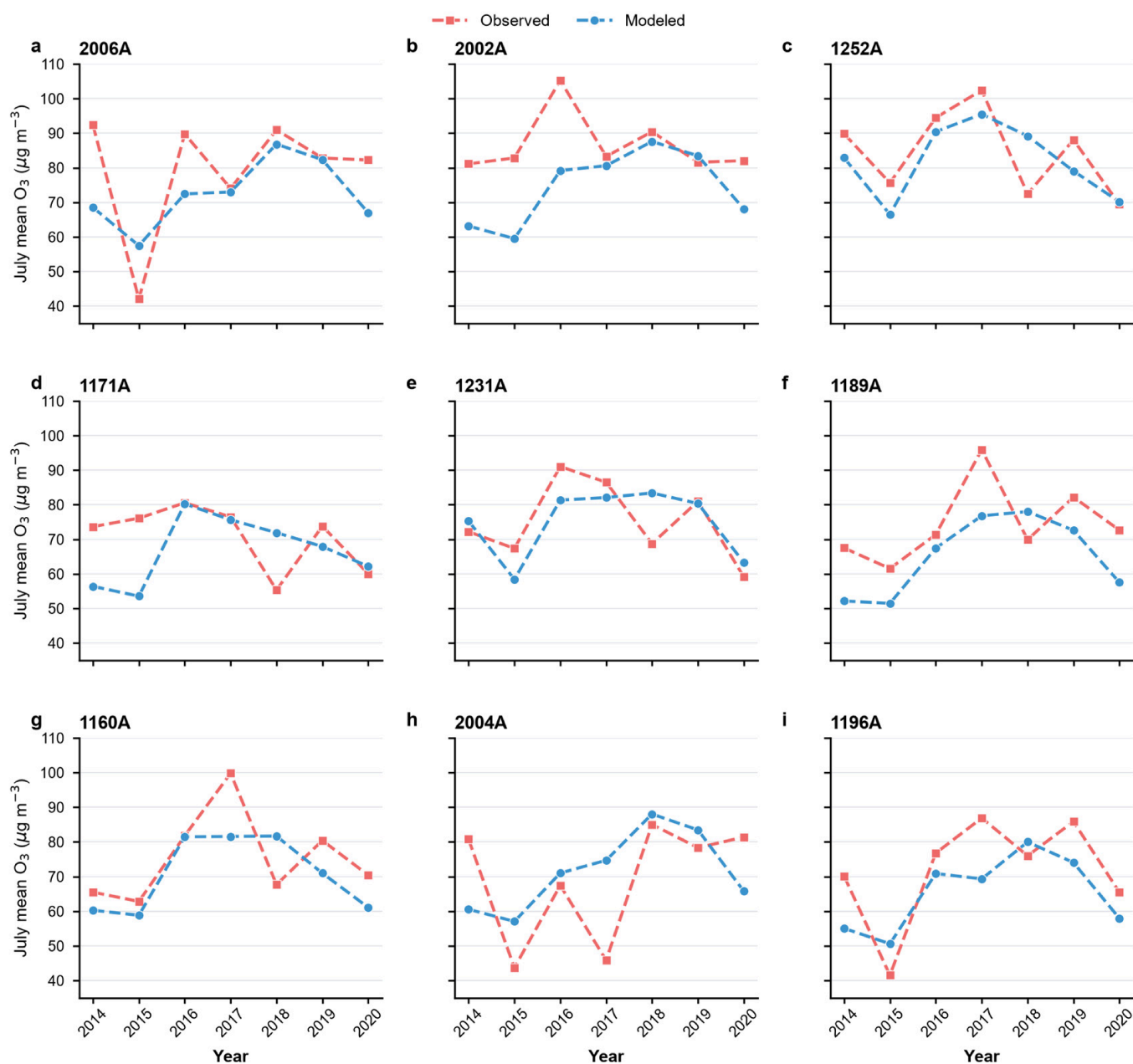


Figure A3. Interannual variations in observed and modeled July mean O₃ concentrations at representative monitoring stations over the YRD during 2014–2020. (a) 2006A; (b) 2002A; (c) 1252A; (d) 1171A; (e) 1231A; (f) 1189A; (g) 1160A; (h) 2004A; (i) 1196A. Red squares and blue circles represent observations and model simulations, respectively.

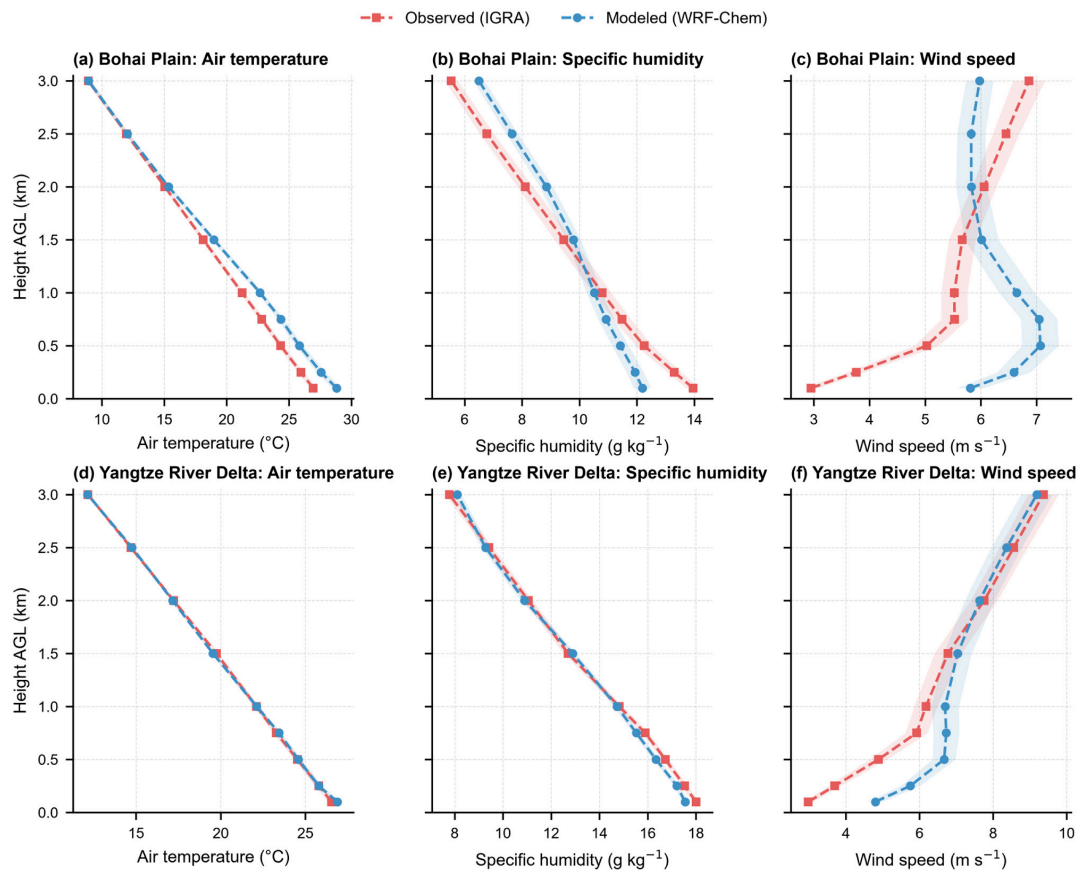


Figure A4. July 2014 mean vertical profiles of air temperature, specific humidity, and wind speed from IGRA radiosonde observations and collocated WRF-Chem simulations over the Bohai Plain and the YRD. The colored shaded bands indicate ± 1 standard error of the mean around the corresponding mean profiles at each altitude.

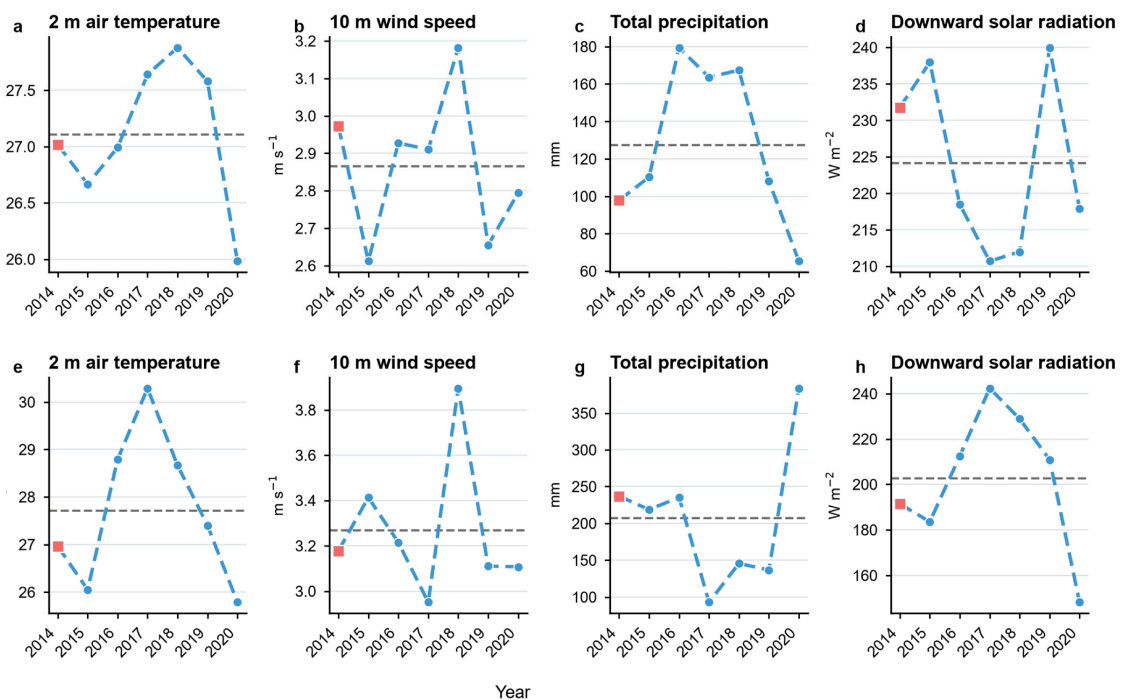


Figure A5. Interannual variations in July meteorological conditions over (a–d) the Bohai Plain and (e–h) the YRD during 2014–2020. The horizontal gray dashed lines indicate the 2014–2020 means for the corresponding variables.

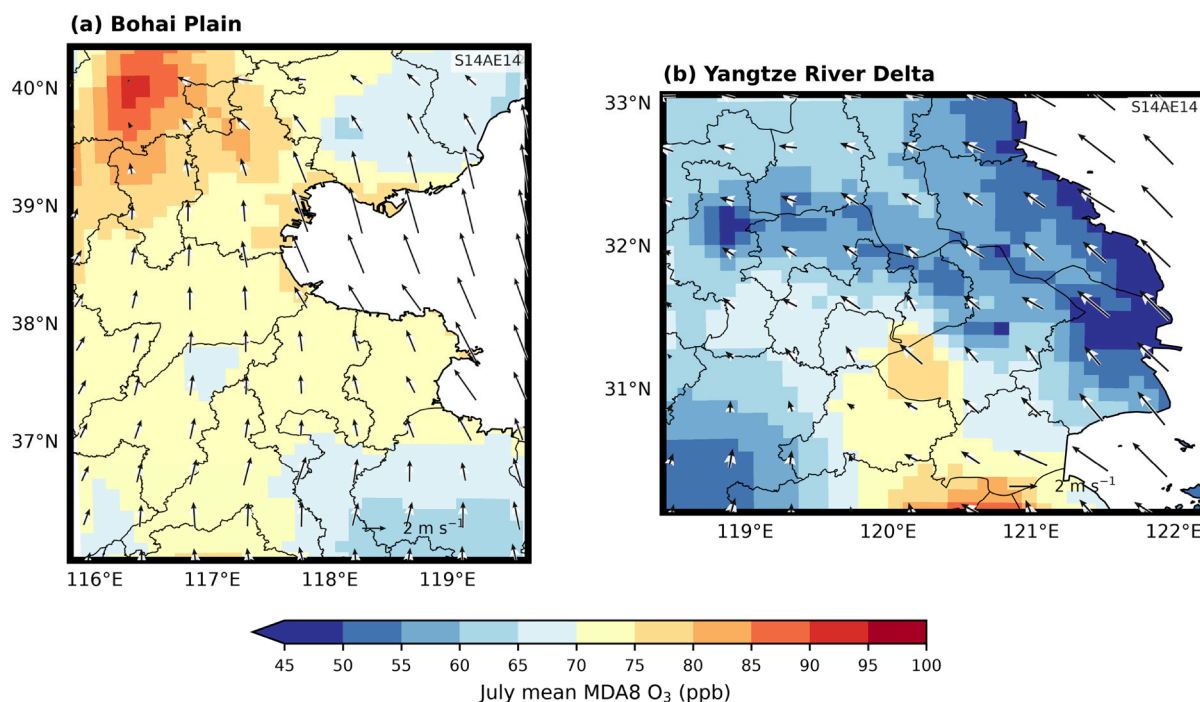


Figure A6. July mean MDA8 O₃ concentrations and 10 m wind fields in the base simulation over (a) the Bohai Plain and (b) the YRD.

References

- Wang, T.; Xue, L.; Brimblecombe, P.; Lam, Y.F.; Li, L.; Zhang, L. Ozone pollution in China: A review of concentrations, meteorological influences, chemical precursors, and effects. *Sci. Total Environ.* **2017**, *575*, 1582–1596. [\[CrossRef\]](#) [\[PubMed\]](#)
- Shang, Y.; Sun, Z.; Cao, J.; Wang, X.; Zhong, L.; Bi, X.; Li, H.; Liu, W.; Zhu, T.; Huang, W. Systematic review of Chinese studies of short-term exposure to air pollution and daily mortality. *Environ. Int.* **2013**, *54*, 100–111. [\[CrossRef\]](#) [\[PubMed\]](#)
- Wang, L.; Bai, Y.; Zhang, F.; Wang, W.; Liu, X.; Krafft, T. Spatiotemporal patterns of ozone and cardiovascular and respiratory disease mortalities due to ozone in Shenzhen. *Sustainability* **2017**, *9*, 559. [\[CrossRef\]](#)
- Moura, B.B.; Alves, E.S.; Marabesi, M.A.; de Souza, S.R.; Schaub, M.; Vollenweider, P. Ozone affects leaf physiology and causes injury to foliage of native tree species from the tropical Atlantic Forest of southern Brazil. *Sci. Total Environ.* **2018**, *610–611*, 912–925. [\[CrossRef\]](#) [\[PubMed\]](#)
- Shimizu, Y.; Lu, Y.; Aono, M.; Omasa, K. A novel remote sensing-based method of ozone damage assessment effect on Net Primary Productivity of various vegetation types. *Atmos. Environ.* **2019**, *217*, 116947. [\[CrossRef\]](#)
- Dang, R.; Liao, H.; Fu, Y. Quantifying the anthropogenic and meteorological influences on summertime surface ozone in China over 2012–2017. *Sci. Total Environ.* **2021**, *754*, 142394. [\[CrossRef\]](#) [\[PubMed\]](#)
- Wei, J.; Li, Z.; Li, K.; Dickerson, R.R.; Pinker, R.T.; Wang, J.; Liu, X.; Sun, L.; Xue, W.; Cribb, M. Full-coverage mapping and spatiotemporal variations of ground-level ozone (O₃) pollution from 2013 to 2020 across China. *Remote Sens. Environ.* **2022**, *270*, 112775. [\[CrossRef\]](#)
- Li, K.; Jacob, D.J.; Liao, H.; Shen, L.; Zhang, Q.; Bates, K.H. Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 422–427. [\[CrossRef\]](#) [\[PubMed\]](#)
- Li, K.; Jacob, D.J.; Shen, L.; Lu, X.; De Smedt, I.; Liao, H. Increases in surface ozone pollution in China from 2013 to 2019: Anthropogenic and meteorological influences. *Atmos. Chem. Phys.* **2020**, *20*, 11423–11433. [\[CrossRef\]](#)
- Sun, L.; Xue, L.; Wang, Y.; Li, L.; Lin, J.; Ni, R.; Yan, Y.; Chen, L.; Li, J.; Zhang, Q.; et al. Impacts of meteorology and emissions on summertime surface ozone increases over central eastern China between 2003 and 2015. *Atmos. Chem. Phys.* **2019**, *19*, 1455–1469. [\[CrossRef\]](#)
- Solomon, P.; Cowling, E.; Hidy, G.; Furiness, C. Comparison of scientific findings from major ozone field studies in North America and Europe. *Atmos. Environ.* **2000**, *34*, 1885–1920. [\[CrossRef\]](#)
- Monks, P.S.; Archibald, A.T.; Colette, A.; Cooper, O.; Coyle, M.; Derwent, R.; Fowler, D.; Granier, C.; Law, K.S.; Mills, G.E.; et al. Tropospheric ozone and its precursors from the urban to the global scale from air quality to short-lived climate forcer. *Atmos. Chem. Phys.* **2015**, *15*, 8889–8973. [\[CrossRef\]](#)
- Tang, G.; Li, X.; Wang, Y.; Xin, J.; Ren, X. Surface ozone trend details and interpretations in Beijing, 2001–2006. *Atmos. Chem. Phys.* **2009**, *9*, 8813–8823. [\[CrossRef\]](#)

14. Xu, J.; Tie, X.; Gao, W.; Lin, Y.; Fu, Q. Measurement and model analyses of the ozone variation during 2006 to 2015 and its response to emission change in megacity Shanghai, China. *Atmos. Chem. Phys.* **2019**, *19*, 9017–9035. [CrossRef]
15. Liu, Y.; Wang, T. Worsening urban ozone pollution in China from 2013 to 2017—Part 2: The effects of emission changes and implications for multi-pollutant control. *Atmos. Chem. Phys.* **2020**, *20*, 6323–6337. [CrossRef]
16. Zong, R.; Yang, X.; Wen, L.; Xu, C.; Zhu, Y.; Chen, T.; Yao, L.; Wang, L.; Zhang, J.; Yang, L.; et al. Strong ozone production at a rural site in the North China Plain: Mixed effects of urban plumes and biogenic emissions. *J. Environ. Sci.* **2018**, *71*, 261–270. [CrossRef] [PubMed]
17. Lu, X.; Ye, X.; Zhou, M.; Zhao, Y.; Weng, H.; Kong, H.; Li, K.; Gao, M.; Zheng, B.; Lin, J.; et al. The underappreciated role of agricultural soil nitrogen oxide emissions in ozone pollution regulation in North China. *Nat. Commun.* **2021**, *12*, 5021. [CrossRef] [PubMed]
18. Shen, Y.; Xiao, Z.; Wang, Y.; Xiao, W.; Yao, L.; Zhou, C. Impacts of agricultural soil NO_x emissions on O₃ over Mainland China. *J. Geophys. Res. Atmos.* **2023**, *128*, e2022JD037986. [CrossRef]
19. Gao, D.; Xie, M.; Liu, J.; Wang, T.; Ma, C.; Bai, H.; Chen, X.; Li, M.; Zhuang, B.; Li, S. Ozone variability induced by synoptic weather patterns in warm seasons of 2014–2018 over the Yangtze River Delta region, China. *Atmos. Chem. Phys.* **2021**, *21*, 5847–5864. [CrossRef]
20. Wang, W.; van der A, R.; Ding, J.; van Weele, M.; Cheng, T. Spatial and temporal changes of the ozone sensitivity in China based on satellite and ground-based observations. *Atmos. Chem. Phys.* **2021**, *21*, 7253–7269. [CrossRef]
21. Zhu, S.; Ma, J.; Wang, S.; Sun, S.; Wang, P.; Zhang, H. Shifts of formation regimes and increases of atmospheric oxidation led to ozone increase in North China Plain and Yangtze River Delta from 2016 to 2019. *J. Geophys. Res. Atmos.* **2023**, *128*, e2022JD038373. [CrossRef]
22. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [CrossRef]
23. Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Horányi, A.; Muñoz-Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Schepers, D.; et al. The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.* **2020**, *146*, 1999–2049. [CrossRef]
24. European Centre for Medium-Range Weather Forecasts. ERA5: Data Documentation. Available online: <https://confluence.ecmwf.int/pages/viewpage.action?pageId=179741903> (accessed on 2 September 2026).
25. Shikhovtsev, M.Y.; Shikhovtsev, A.Y.; Lezhenin, A.A.; Gradov, V.S.; Khaikin, V.B.; Kirichenko, K.E.; Kovadlo, P.G. WRF model estimation of precipitable water vapor over the Sayan Solar Observatory and Khulugaysha Peak. *Atmos. Ocean. Opt.* **2026**, *39*, 355–361. [CrossRef]
26. Durre, I.; Yin, X.; Vose, R.S.; Applequist, S.; Arnfield, J.; Korzeniewski, B.; Hundermark, B. *Integrated Global Radiosonde Archive (IGRA), Version 2*; NOAA National Centers for Environmental Information: Asheville, NC, USA, 2016. [CrossRef]
27. Yang, Z.; Li, Z.; Cheng, F.; Lv, Q.; Li, K.; Zhang, T.; Zhou, Y.; Zhao, B.; Xue, W.; Wei, J. Two-decade surface ozone (O₃) pollution in China: Enhanced fine-scale estimations and environmental health implications. *Remote Sens. Environ.* **2025**, *317*, 114459. [CrossRef]
28. He, Y.; Feng, J.; Wang, J.; Cao, L. Constraining the uncertainty of urbanization effect on surface air temperature change over the Beijing-Tianjin-Hebei region in China. *Atmos. Sci. Lett.* **2023**, *24*, e1160. [CrossRef]
29. Grell, G.A.; Peckham, S.E.; Schmitz, R.; McKeen, S.A.; Frost, G.; Skamarock, W.C.; Eder, B. Fully coupled “online” chemistry within the WRF model. *Atmos. Environ.* **2005**, *39*, 6957–6975. [CrossRef]
30. Zaveri, R.A.; Peters, L.K. A new lumped structure photochemical mechanism for large-scale applications. *J. Geophys. Res. Atmos.* **1999**, *104*, 30387–30415. [CrossRef]
31. Lin, Y.-L.; Farley, R.D.; Orville, H.D. Bulk parameterization of the snow field in a cloud model. *J. Clim. Appl. Meteorol.* **1983**, *22*, 1065–1092. [CrossRef] [PubMed]
32. Chou, M.-D.; Suarez, M.J.; Ho, C.-H.; Yan, M.M.-H.; Lee, K.-T. Parameterizations for cloud overlapping and shortwave single-scattering properties for use in general circulation and cloud ensemble models. *J. Clim.* **1998**, *11*, 202–214. [CrossRef]
33. Mlawer, E.J.; Taubman, S.J.; Brown, P.D.; Iacono, M.J.; Clough, S.A. Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. *J. Geophys. Res. Atmos.* **1997**, *102*, 16663–16682. [CrossRef]
34. Chen, F.; Dudhia, J. Coupling an advanced land surface-hydrology model with the Penn State-NCAR MM5 modeling system. Part I: Model implementation and sensitivity. *Mon. Weather Rev.* **2001**, *129*, 569–585. [CrossRef]
35. Hong, S.-Y.; Noh, Y.; Dudhia, J. A new vertical diffusion package with an explicit treatment of entrainment processes. *Mon. Weather Rev.* **2006**, *134*, 2318–2341. [CrossRef]
36. Kain, J.S. The Kain-Fritsch convective parameterization: An update. *J. Appl. Meteorol.* **2004**, *43*, 170–181. [CrossRef] [PubMed]
37. Zaveri, R.A.; Easter, R.C.; Fast, J.D.; Peters, L.K. Model for simulating aerosol interactions and chemistry (MOSAIC). *J. Geophys. Res. Atmos.* **2008**, *113*, D13204. [CrossRef]
38. Madronich, S.; Flocke, S. The role of solar radiation in atmospheric chemistry. In *Environmental Photochemistry*; Springer: Berlin/Heidelberg, Germany, 1999; pp. 1–26. [CrossRef]

39. Jiménez, P.A.; Dudhia, J.; González-Rouco, J.F.; Navarro, J.; Montávez, J.P.; García-Bustamante, E. A revised scheme for the WRF surface layer formulation. *Mon. Weather Rev.* **2012**, *140*, 898–918. [\[CrossRef\]](#)
40. Jia, W.; Zhang, X.; Wang, H.; Wang, Y.; Wang, D.; Zhong, J.; Zhang, W.; Zhang, L.; Guo, L.; Lei, Y.; et al. Comprehensive evaluation of typical planetary boundary layer (PBL) parameterization schemes in China—Part 1: Understanding expressiveness of schemes for different regions from the mechanism perspective. *Geosci. Model Dev.* **2023**, *16*, 6635–6670. [\[CrossRef\]](#)
41. Yang, Y.; Zhou, Y.; Wang, H.; Li, M.; Li, H.; Wang, P.; Yue, X.; Li, K.; Zhu, J.; Liao, H. Meteorological characteristics of extreme ozone pollution events in China and their future predictions. *Atmos. Chem. Phys.* **2024**, *24*, 1177–1191. [\[CrossRef\]](#)
42. Wang, P.; Yang, Y.; Li, H.; Chen, L.; Dang, R.; Xue, D.; Li, B.; Tang, J.; Leung, L.R.; Liao, H. North China Plain as a hot spot of ozone pollution exacerbated by extreme high temperatures. *Atmos. Chem. Phys.* **2022**, *22*, 4705–4719. [\[CrossRef\]](#)
43. Boylan, J.W.; Russell, A.G. PM and light extinction model performance metrics, goals, and criteria for three-dimensional air quality models. *Atmos. Environ.* **2006**, *40*, 4946–4959. [\[CrossRef\]](#)
44. Yu, E.; Bai, R.; Chen, X.; Shao, L. Impact of physical parameterizations on wind simulation with WRF V3.9.1.1 under stable conditions at planetary boundary layer gray-zone resolution: A case study over the coastal regions of North China. *Geosci. Model Dev.* **2022**, *15*, 8111–8134. [\[CrossRef\]](#)
45. Lu, X.; Zhang, L.; Chen, Y.; Zhou, M.; Zheng, B.; Li, K.; Liu, Y.; Lin, J.; Fu, T.-M.; Zhang, Q. Exploring 2016–2017 surface ozone pollution over China: Source contributions and meteorological influences. *Atmos. Chem. Phys.* **2019**, *19*, 8339–8361. [\[CrossRef\]](#)
46. Kim, K.-M.; Kim, S.-W.; Seo, S.; Blake, D.R.; Cho, S.; Crawford, J.H.; Emmons, L.K.; Fried, A.; Herman, J.R.; Hong, J.; et al. Sensitivity of the WRF-Chem v4.4 simulations of ozone and formaldehyde and their precursors to multiple bottom-up emission inventories over East Asia during the KORUS-AQ 2016 field campaign. *Geosci. Model Dev.* **2024**, *17*, 1931–1955. [\[CrossRef\]](#)
47. Lv, Z.; Wei, W.; Cheng, S.; Han, X.; Wang, X. Meteorological characteristics within boundary layer and its influence on PM_{2.5} pollution in six cities of North China based on WRF-Chem. *Atmos. Environ.* **2020**, *228*, 117417. [\[CrossRef\]](#)
48. Wang, L.; Li, M.; Yu, S.; Chen, X.; Li, Z.; Zhang, Y.; Jiang, L.; Xia, Y.; Li, J.; Liu, W.; et al. Unexpected rise of ozone in urban and rural areas, and sulfur dioxide in rural areas during the coronavirus city lockdown in Hangzhou, China: Implications for air quality. *Environ. Chem. Lett.* **2020**, *18*, 1713–1723. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Yin, H.; Liu, C.; Hu, Q.; Liu, T.; Wang, S.; Gao, M.; Xu, S.; Zhang, C.; Su, W. Opposite impact of emission reduction during the COVID-19 lockdown period on the surface concentrations of PM_{2.5} and O₃ in Wuhan, China. *Environ. Pollut.* **2021**, *289*, 117899. [\[CrossRef\]](#) [\[PubMed\]](#)
50. Yin, H.; Lu, X.; Sun, Y.; Li, K.; Gao, M.; Zheng, B.; Liu, C. Unprecedented decline in summertime surface ozone over eastern China in 2020 comparably attributable to anthropogenic emission reductions and meteorology. *Environ. Res. Lett.* **2021**, *16*, 124069. [\[CrossRef\]](#)
51. Zhu, J.; Chen, L.; Liao, H.; Yang, H.; Yang, Y.; Yue, X. Enhanced PM_{2.5} decreases and O₃ increases in China during COVID-19 lockdown by aerosol-radiation feedback. *Geophys. Res. Lett.* **2021**, *48*, e2020GL090260. [\[CrossRef\]](#) [\[PubMed\]](#)
52. Cao, J.; Qiu, X.; Liu, Y.; Yan, X.; Gao, J.; Peng, L. Identifying the dominant driver of elevated surface ozone concentration in North China plain during summertime 2012–2017. *Environ. Pollut.* **2022**, *300*, 118912. [\[CrossRef\]](#) [\[PubMed\]](#)
53. Mao, Y.-H.; Yu, S.; Shang, Y.; Liao, H.; Li, N. Response of summer ozone to precursor emission controls in the Yangtze River Delta region. *Front. Environ. Sci.* **2022**, *10*, 864897. [\[CrossRef\]](#)
54. Steinbrecht, W.; Kubistin, D.; Plass-Dülmer, C.; Davies, J.; Tarasick, D.W.; von der Gathen, P.; Deckelmann, H.; Jepsen, N.; Kivi, R.; Lyall, N.; et al. COVID-19 crisis reduces free tropospheric ozone across the Northern Hemisphere. *Geophys. Res. Lett.* **2021**, *48*, e2020GL091987. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Sillman, S. The use of NO_y, H₂O₂, and HNO₃ as indicators for ozone-NO_x-hydrocarbon sensitivity in urban locations. *J. Geophys. Res. Atmos.* **1995**, *100*, 14175–14188. [\[CrossRef\]](#)
56. Hammer, M.-U.; Vogel, B.; Vogel, H. Findings on H₂O₂/HNO₃ as an indicator of ozone sensitivity in Baden-Württemberg, Berlin-Brandenburg, and the Po Valley based on numerical simulations. *J. Geophys. Res. Atmos.* **2002**, *107*, 8190. [\[CrossRef\]](#)
57. Sha, T.; Yang, S.; Chen, Q.; Li, L.; Ma, X.; Zhang, Y.-L.; Feng, Z.; Boersma, K.F.; Wang, J. Large contributions of soil emissions to the atmospheric nitrogen budget and their impacts on air quality and temperature rise in North China. *Atmos. Chem. Phys.* **2024**, *24*, 8441–8455. [\[CrossRef\]](#)
58. Du, X.; Tang, W.; Cheng, M.; Zhang, Z.; Li, Y.; Li, Y.; Meng, F. Modeling of spatial and temporal variations of ozone-NO_x-VOC sensitivity based on photochemical indicators in China. *J. Environ. Sci.* **2022**, *114*, 454–464. [\[CrossRef\]](#) [\[PubMed\]](#)
59. Li, K.; Jacob, D.J.; Liao, H.; Zhu, J.; Shah, V.; Shen, L.; Bates, K.H.; Zhang, Q.; Zhai, S. A two-pollutant strategy for improving ozone and particulate air quality in China. *Nat. Geosci.* **2019**, *12*, 906–910. [\[CrossRef\]](#)
60. Atkinson, R. Atmospheric chemistry of VOCs and NO_x. *Atmos. Environ.* **2000**, *34*, 2063–2101. [\[CrossRef\]](#)
61. Tang, K.; Zhang, H.; Feng, W.; Liao, H.; Hu, J.; Li, N. Increasing but variable trend of surface ozone in the Yangtze River Delta region of China. *Front. Environ. Sci.* **2022**, *10*, 836191. [\[CrossRef\]](#)
62. Liu, Y.; Geng, G.; Cheng, J.; Liu, Y.; Xiao, Q.; Liu, L.; Shi, Q.; Tong, D.; He, K.; Zhang, Q. Drivers of increasing ozone during the two phases of clean air actions in China 2013–2020. *Environ. Sci. Technol.* **2023**, *57*, 8954–8964. [\[CrossRef\]](#) [\[PubMed\]](#)

63. Wang, Y.; Zhao, Y.; Liu, Y.; Jiang, Y.; Zheng, B.; Xing, J.; Liu, Y.; Wang, S.; Nielsen, C.P. Sustained emission reductions have restrained the ozone pollution over China. *Nat. Geosci.* **2023**, *16*, 967–974. [[CrossRef](#)]
64. Fang, J.; Zhang, Y.; Hauglustaine, D.; Zheng, B.; Wang, M.; Li, J.; Sun, Y.; Li, H.; Wang, J.; Wu, Y.; et al. Tracking surface ozone responses to clean air actions under a warming climate in China using machine learning. *Atmos. Chem. Phys.* **2026**, *26*, 851–867. [[CrossRef](#)]
65. Dai, J.; Brasseur, G.P.; Vrekoussis, M.; Kanakidou, M.; Qu, K.; Zhang, Y.; Zhang, H.; Wang, T. The atmospheric oxidizing capacity in China—Part 1: Roles of different photochemical processes. *Atmos. Chem. Phys.* **2023**, *23*, 14127–14158. [[CrossRef](#)]
66. Dai, J.; Brasseur, G.P.; Vrekoussis, M.; Kanakidou, M.; Qu, K.; Zhang, Y.; Zhang, H.; Wang, T. The atmospheric oxidizing capacity in China—Part 2: Sensitivity to emissions of primary pollutants. *Atmos. Chem. Phys.* **2024**, *24*, 12943–12962. [[CrossRef](#)]
67. Han, X.; Zhu, L.; Wang, S.; Meng, X.; Zhang, M.; Hu, J. Modeling study of impacts on surface ozone of regional transport and emissions reductions over North China Plain in summer 2015. *Atmos. Chem. Phys.* **2018**, *18*, 12207–12221. [[CrossRef](#)]
68. Lyu, X.; Wang, N.; Guo, H.; Xue, L.; Jiang, F.; Zeren, Y.; Cheng, H.; Cai, Z.; Han, L.; Zhou, Y. Causes of a continuous summertime O₃ pollution event in Jinan, a central city in the North China Plain. *Atmos. Chem. Phys.* **2019**, *19*, 3025–3042. [[CrossRef](#)]
69. Zheng, Y.; Jiang, F.; Feng, S.; Shen, Y.; Liu, H.; Guo, H.; Lyu, X.; Jia, M.; Lou, C. Large-scale land-sea interactions extend ozone pollution duration in coastal cities along northern China. *Environ. Sci. Ecotechnol.* **2024**, *18*, 100322. [[CrossRef](#)] [[PubMed](#)]
70. Zhu, X.; Tang, G.; Guo, J.; Hu, B.; Song, T.; Wang, L.; Xin, J.; Gao, W.; Münkel, C.; Schäfer, K.; et al. Mixing layer height on the North China Plain and meteorological evidence of serious air pollution in southern Hebei. *Atmos. Chem. Phys.* **2018**, *18*, 4897–4910. [[CrossRef](#)]
71. Liu, H.; Han, X.; Tang, G.; Zhang, J.; Xia, X.A.; Zhang, M.; Meng, L. Model analysis of vertical exchange of boundary layer ozone and its impact on surface air quality over the North China Plain. *Sci. Total Environ.* **2022**, *821*, 153436. [[CrossRef](#)] [[PubMed](#)]
72. Shikhovtsev, M.Y.; Shikhovtsev, A.Y.; Kovadlo, P.G.; Obolkin, V.A.; Molozhnikova, Y.V. Influence of air movement structure on microphysical properties of the atmosphere over Listvyanka. *Atmos. Ocean. Opt.* **2025**, *38*, 180–187. [[CrossRef](#)]
73. Wang, J.; Gao, J.; Che, F.; Yang, X.; Yang, Y.; Liu, L.; Xiang, Y.; Li, H. Summertime response of ozone and fine particulate matter to mixing layer meteorology over the North China Plain. *Atmos. Chem. Phys.* **2023**, *23*, 14715–14733. [[CrossRef](#)]
74. Li, L.; An, J.; Huang, L.; Yan, R.; Huang, C.; Yarwood, G. Ozone source apportionment over the Yangtze River Delta region, China: Investigation of regional transport, sectoral contributions and seasonal differences. *Atmos. Environ.* **2019**, *202*, 269–280. [[CrossRef](#)]
75. Shu, L.; Wang, T.; Han, H.; Xie, M.; Chen, P.; Li, M.; Wu, H. Summertime ozone pollution in the Yangtze River Delta of eastern China during 2013–2017: Synoptic impacts and source apportionment. *Environ. Pollut.* **2020**, *257*, 113631. [[CrossRef](#)] [[PubMed](#)]
76. Sillman, S. The relation between ozone, NO_x and hydrocarbons in urban and polluted rural environments. *Atmos. Environ.* **1999**, *33*, 1821–1845. [[CrossRef](#)]
77. Shen, Y.; Yang, T.; Liang, X.; Liu, S.; Xia, L.; Chen, N. How coarse analysis can obscure key trends—A multi-scale study using very high-resolution intra-urban land data. *Geo-Spat. Inf. Sci.* **2025**, *28*, 3016–3035. [[CrossRef](#)]

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