JGR Atmospheres

RESEARCH ARTICLE
10.1029/2020JD033519

# Source Apportionment of Regional Ozone Pollution Observed at Mount Tai, North China: Application of Lagrangian Photochemical Trajectory Model and Implications for Control Policy

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**Key Points:**

- The Lagrangian photochemical trajectory model is capable of tracking the sources of regional $O_3$ pollution at receptor site
- The North China Plain was the major origin of regional $O_3$ at Mt. Tai with an average contribution of 74 ± 27%
- Nocturnal $O_3$ at Mount Tai is a good indicator for predicting surface $O_3$ pollution over a wide spatial coverage

**Supporting Information:**

- Supporting Information S1
- Supporting Information S2

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**Citation:**
Zhang, Y., Xue, L., Li, H., Chen, T., Mu, J., Dong, C., et al. (2021). Source apportionment of regional ozone pollution observed at Mount Tai, North China: Application of Lagrangian photochemical trajectory model and implications for control policy. *Journal of Geophysical Research: Atmospheres*, *126*, e2020JD033519. https://doi.org/10.1029/2020JD033519

Received 14 JUL 2020
Accepted 5 DEC 2020



**Abstract** To better understand the characteristics and trace the sources of regional ozone ($O_3$) in the North China Plain (NCP), we analyzed 1-year continuous observations obtained at Mount Tai in 2018 and compared with previous data from 2006–2009. In the warm seasons (April–September), $O_3$ pollution (defined as a maximum daily 8-h average $O_3$ mixing ratio that exceeds 75 ppbv) occurred frequently (59%–92% of days) and $O_3$ concentrations significantly increased (especially in July–September) from 2006–2009 to 2018. We applied the Lagrangian photochemical trajectory model, built on the coupling of the Lagrangian backward trajectory model and Master Chemical Mechanism box model, to identify the source regions, key precursors, and emission sectors. The NCP was identified as the major source region with an average contribution of 74% ± 27% to the regional $O_3$ concentrations during the $O_3$ episodes in April–September. Regional $O_3$ formation was highly NOx-sensitive in air masses traveling from the southern part of the NCP but limited by anthropogenic hydrocarbons (especially alkenes) in air masses from the northern part of the NCP. The reduction of emissions from transportation and industry sectors would significantly reduce the regional $O_3$ concentrations. Biomass burning also exerts a significant influence on regional $O_3$ concentrations under certain circumstances. This study demonstrates that the regional background $O_3$ at mountaintop levels is a good indicator of surface $O_3$ pollution over a wide spatial coverage, and provides guidance for regional collaboration on emission control to mitigate photochemical air pollution over the NCP.

## 1. Introduction

Tropospheric ozone ($O_3$) is an important trace gas in the ambient air. The photolysis of $O_3$ in the troposphere provides an important primary source of the hydroxyl radical (OH), which initiates the chemical oxidation cycle (Lelieveld et al., 2008). Tropospheric $O_3$ serves as an important greenhouse gas that contributes to global warming (IPCC, 2013; Monks et al., 2015), and long-term exposure to high concentrations of surface $O_3$ is harmful to human health and vegetation (Fuhrer, 2009). Surface $O_3$ pollution has become a major environmental concern in China in recent decades (Wang, Xue, et al., 2017; and references therein; Xue, Wang, Gao, et al., 2014), and the increasing trends shown in several long-term studies provide evidence that the situation is worsening (Lu et al., 2018, 2020; Sun et al., 2016; Wang et al., 2019; Wang, Wei, Ding, et al, 2009; Xu et al., 2020). In contrast, the pollution by other routinely monitored pollutants (e.g., $SO_2$, $NO_2$, CO, $PM_{2.5}$, and $PM_{10}$) has significantly improved since 2013 (http://www.mee.gov.cn; Liu & Wang, 2020; Zheng et al., 2018). A clear understanding of the source apportionment of regional $O_3$ pollution is therefore critical for future air quality management in China.

In polluted urban areas, surface $O_3$ can be rapidly produced by photochemical reactions of volatile organic compounds (VOCs) and NOx (NOx = NO + $NO_2$). The $O_3$ can then be transported downwind to rural or remote areas and lead to regional $O_3$ pollution (Wang, Xue, et al., 2017; and references therein). The challenges of tracking regional $O_3$ pollution sources primarily exist in two aspects (Cooper et al., 2015; Schroeder et al., 2020). First, the formation mechanism of $O_3$ is complex and there is a highly nonlinear

relationship between $O_3$ and its precursors (VOCs and NOx), which poses difficulties for the accurate representation of $O_3$ formation using the chemical mechanisms in current models (Lyu et al., 2019; Xue, Wang, Gao, et al., 2014). The second challenge is the coupling of the regional transport and nonlinear chemistry between $O_3$ and its precursors (Xiao et al., 2010; Yang et al., 2019). For example, the $O_3$ in the receptor area may be sensitive to NOx (VOCs) locally and sensitive to VOCs (NOx) in the upwind areas. Decoupling of the regional transport and $O_3$-precursor relationship therefore presents a major challenge for current atmospheric research and air pollution control.

The North China Plain (NCP) is one of China's most rapidly developing regions and has experienced severe $O_3$ pollution in recent decades. Several studies have examined $O_3$ pollution characteristics, formation regimes, and source apportionment (Wang, Xue, et al., 2017; and references therein). In summer, high $O_3$ episodes (defined in this study as a maximum daily 8-h average $O_3$ mixing ratio (MDA8 $O_3$) that exceeds 75 ppbv) have occurred frequently in various environments covering urban, suburban, rural, and mountainous sites (Chen et al., 2020; Lyu et al., 2019; Ma et al., 2019; Sun et al., 2016; Wei et al., 2015; Zong et al., 2018). The maximum hourly $O_3$ concentration at a rural site downwind of Beijing reached as high as 286 ppbv in June–July 2005 (Wang et al., 2006) and long-term trend analyses have confirmed the rapid increase of regional $O_3$ concentrations (Sun et al, 2016, 2019; Xu et al., 2020). Many observation-based modeling studies have shown that $O_3$ formation in urban areas generally tended to be VOC-limited, whereas that in rural areas tended to be NOx-limited (Wang, Xue, et al., 2017). Some studies have also addressed $O_3$-precursor relationships over a large regional scale. Xing et al. (2011) examined the nonlinear response of $O_3$ to precursor emission reductions and found that regional sources were significant contributors to $O_3$ concentrations in Beijing and that the reduction of local emissions (even by 80%) in Beijing alone would be insufficient to resolve regional $O_3$ pollution. Xue, Wang, Louie, et al. (2014) also pointed out that increased regional transport negated the local control efforts in Hong Kong, southern China. These studies demonstrate the necessity of synchronous control on regional emissions over most areas of China.

Numerical models coupled with complex chemical mechanisms (especially zero-dimensional [0-D] and three-dimensional [3-D] models) have been widely used to track $O_3$ sources. Both model types have advantages and disadvantages. Specifically, 0-D models generally adopt detailed chemical mechanisms but only consider chemical processes, with little to no consideration of important physical processes, such as vertical and horizontal transport. As a result, 0-D models can reproduce the in situ chemistry of $O_3$ but their applications are largely limited by their small spatial representativeness (Chen et al., 2020; Ling et al., 2014; Lyu et al., 2016; Xue, Wang, Gao, et al., 2014). In comparison, 3-D models incorporate meteorological fields and can track $O_3$ sources at different spatial scales. Some source apportionment modules, such as Ozone Source Apportionment Technology, Decoupled Direct Method in three Dimensions, and Brute Force within 3-D air quality models, can provide detailed information on the source-receptor relationships of $O_3$ (Li et al., 2012; Xiao et al., 2010; Yang et al., 2019); however, their application tends to substantially increase the computational cost. As a result, 3-D models generally incorporate simplified chemical mechanisms as a compromise. In addition to 0-D and 3-D models, a photochemical trajectory model (PTM), which consists of a moving box of specific dimensions and detailed chemical mechanisms (e.g., Master Chemical Mechanism [MCM]), has been widely applied to describe regional-scale $O_3$ pollution in Europe (Derwent & Jenkin, 1991; Hough & Derwent, 1987). In this study, we improved the PTM construction as well as the physical and chemical modules, and built a Lagrangian PTM (LPTM) by coupling both a Lagrangian backward trajectory model (Draxler et al., 2018) and MCM box model (Jenkin et al., 2003; Saunders et al., 2003). The efficacy of the LPTM was verified by tracking regional $O_3$ sources on the premise of accurate decoupling of the regional transport and $O_3$-precursor relationship.

In this study, we analyzed the recent 1-year (2018) continuous observations of $O_3$ and related parameters at Mount Tai with a combination of LPTM simulations to better understand the causes of the severe regional $O_3$ pollution over the NCP. We first present the $O_3$ pollution characteristics observed in 2018 and compare with data from 2006 to 2009. We then track the origins of the $O_3$ precursors and quantify the contributions of different source regions to high regional $O_3$ concentrations using the LPTM. A series of sensitivity experiments were conducted to diagnose the key precursors and emission sectors over the major source regions. We also demonstrate the strong relationship between the regional $O_3$ background at mountaintop levels

and regional ground-level $O_3$ pollution, and make recommendations for regionally coordinated $O_3$ control strategies.

## 2. Materials and Methods

### 2.1. Observational Data Set

Field observations were conducted at the Taishan National Reference Climatological Station located on the summit of Mount Tai (36.26°N, 117.11°E) at an altitude of 1,534 m above sea level. Because of its high elevation, this site is rarely impacted by local anthropogenic emissions and data collected there well reflect regional $O_3$ pollution of the NCP. As a typical mountain site, Mount Tai is frequently influenced by the mountain-valley breezes. During the daytime, the valley breezes and evolution of the planetary boundary layer (PBL) bring the air pollutants from the valley to the mountaintop, while the air masses at nighttime are governed by the downslope transport and long-range transport of regional air in the free troposphere or the residual layer (Gao et al., 2005; Sun et al., 2016). Therefore, nocturnal $O_3$ data at Mount Tai were used to represent the regional background $O_3$ concentrations considering the small impact of NO titration on the mountaintop. This site is operated by Shandong University and continuously measures major trace gases and aerosol properties. In this study, we analyzed the 1-year continuous measurements from January 1, 2018 until December 31, 2018. Previous data collected from January 2006 to July 2009 were also analyzed for comparison to examine the decadal changes of regional $O_3$ concentrations (Sun et al., 2016).

Real-time measurements of trace gases, including $O_3$, NO, $NO_2$, NOy (NOy = NO + $NO_2$ + $NO_3$ + $N_2O_5$ + HONO + $HNO_3$ + $NO_3^-$ + PANs + $RONO_2$ + etc.), and CO, were implemented using standard commercial techniques (Li et al., 2020). $O_3$ was measured by a model T400 UV photometric ozone analyzer (Teledyne Advanced Pollution Instrumentation (T-API)) with a detection limit of 0.4 ppbv and precision of 0.5%. NO and NOy were monitored using a chemiluminescence analyzer (model T200U, T-API) with a detection limit of 0.4 ppbv and precision of 0.5%. NOy was converted to NO by an externally placed molybdenum oxide converter prior to detection. $NO_2$ was monitored by an optical analyzer (model T500U, T-API) with a detection limit of 40 pptv and precision of 0.5%. CO was measured by gas filter correlation and non-dispersive infrared analyzers. From January 1, 2018 to July 30, 2018, CO was measured using a model 300 optical analyzer (T-API) with a detection limit of 50 ppbv and precision of 0.5%. From July 31, 2018 to December 31, 2018, CO was measured using a model T300U optical analyzer (T-API) with a detection limit of 20 ppbv and precision of 0.5%. During the measurements, these analyzers were routinely calibrated for the 1-year continuous observations in 2018. Multi-point calibrations were performed monthly and zero and span calibrations were performed weekly except for the CO analyzer. For CO, multi-point calibrations were performed monthly and the baseline was determined every 8 h by passing ambient air through the internal CO scrubber for 15 min. The calibration system and procedures have been described in detail by Li et al. (2020). Meteorological parameters including ambient temperature and relative humidity (RH) were obtained from the Taishan National Reference Climatological Station.

### 2.2. Lagrangian Photochemical Trajectory Model

Photochemistry during regional transport was reproduced using the LPTM, which was built based on the coupling of the Lagrangian backward trajectory model with the chemical box model. The LPTM consists of five major modules: input; initialization; physical; chemical; and output. The input module was called to read in the gridded emission rates of primary pollutants ( non-methane VOCs [NMVOCs], NOx, CO, and $SO_2$) and meteorological parameters (temperature and RH). The initialization module was used to set the initial concentrations of major pollutants ($O_3$, NMVOCs, NOx, CO, and $SO_2$) and initialize the meteorological parameters (temperature, RH, and the PBL height). The physical and chemical modules incorporated complex physical and chemical processes, respectively. The output module outputted the selected species' concentrations and reaction rates. To provide a realistic description of the air exchange between air masses below the PBL and within the residual layers, the LPTM model was split into two layers vertically, with the upper layer describing the pollutant behavior within the residual layers and the lower layer receiving the ground-level primary emissions (Derwent & Jenkin, 1991). It should be noted that such a coarse vertical

resolution of model may inevitably introduce some uncertainties to the model representation of emissions and dilution mixing within the PBL.

The applied homogeneous chemical mechanism was the state-of-the-art MCM version 3.3.1 (MCMv3.3.1; http://mcm.leeds.ac.uk/MCM/; Jenkin et al., 2003; Saunders et al., 2003), which near-explicitly describes the reactions of 143 VOC species and has been widely used to reproduce the nonlinear chemistry between $O_3$ and its precursors in the atmosphere (Chen et al., 2020; Xue, Wang, Gao, et al., 2014). In addition to homogeneous chemistry, heterogeneous chemistry including $N_2O_5$ hydrolysis, $HO_2$ loss on aerosols, and HONO formation from $NO_2$ surface reactions were also considered in this model (Xue et al., 2016; Xue, Wang, Gao, et al., 2014). The heterogeneous chemical processes were disabled in this study. In addition to the complete chemistry, we also incorporated physical processes, including regional transport, solar radiation, diurnal evolution of the PBL, dry deposition, and air exchange between the air masses and residual layers. The regional transport was incorporated by backward trajectories. The solar radiation was calculated as a function of solar zenith angle under the assumption of clear sky conditions (Hayman, 1997). The PBL height was parameterized to rise linearly from the minimum height at 06:00 local time (LT) to the maximum height at 14:00 LT, remained constant at its maximum in the afternoon, and reduced to the minimum at 20:00 LT. The minimum and maximum heights were constrained using the data obtained by running the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT, v4.9; Draxler et al., 2018). Dry deposition velocities of inorganic gases, peroxyacetyl nitrates, and oxygenated hydrocarbons were parameterized based on the work of Zhang et al. (2003). Air exchange between the air masses and residual layers only occurred when the PBL expanded in the morning, and the pollutant concentrations within the residual layers were set to the concentrations at 21:00 LT from the previous night (Derwent & Jenkin, 1991; Hough & Derwent, 1987). Dry deposition and air exchange between the air masses and residual layers were disabled when the trajectory was above the PBL. The major objective of this study is to quantify the contributions of $O_3$ precursor emissions and the $O_3$-precursor relationships from the specific source regions to the observed $O_3$ pollution at Mt. Tai with the LPTM. The potential impacts of transboundary transport from outside China and stratospheric intrusion were beyond the scope of this study and were not considered here.

We considered three types of primary emission sources: anthropogenic emissions; biogenic emissions; and biomass burning. The anthropogenic emissions (NMVOCs, NOx, CO, and $SO_2$) were derived from the MEIC inventory (Multi-resolution Emission Inventory for China; 0.25° × 0.25°; monthly resolution in 2016; http://www.meicmodel.org/; Li et al., 2014). The biogenic emissions (CO, isoprene, α-pinene, β-pinene, and limonene) were derived from the MEGANv2.1 inventory (https://bai.ess.uci.edu/megan/versions/megan21; 0.5° × 0.5°; monthly resolution in 2010; Sindelarova et al., 2014). The biomass burning emissions (NO, CO, $SO_2$, ethane, propane, ethyne, ethene, propene, benzene, toluene, formaldehyde, acetaldehyde, and Methyl ethyl ketone) were derived from Global Fire Emission Database (0.25° × 0.25°; monthly resolution in 2018; http://www.globalfiredata.org/; Akagi et al., 2011; Andreae & Merlet, 2001). These three inventories contain six principal emission sectors: power, industry, residential, transportation, biomass burning, and biogenic emissions. For biomass burning and biogenic emissions, the emission profile of contained individual NMVOC species was directly obtained from the corresponding inventories. For anthropogenic emissions, which represent the first four emission sectors, a ratio of 9:1 was used to allocate NOx into NO and $NO_2$. Besides, the emission profile of individual NMVOC species from a given anthropogenic emission sector was obtained from previous studies and the US Environmental Protection Agency (USEPA) SPECIATE 4.5 database (Li et al., 2014; Liu, Shao, Fu, et al, 2008; Liu, Shao, Lu, et al., 2008; Simon et al., 2010; Tsai et al., 2003; Wang, Wei, Du, et al., 2009; Yuan et al., 2010; Zheng et al., 2009). Table S1 presents the detailed fractional emissions of major NMVOC species from the different anthropogenic emission sectors. The overall emission rate (unit: molecules/$cm^3$/s) of each pollutant within a grid cell was calculated as follows. The species profile of each emission sector was first multiplied by its total emissions, the emission rate was then calculated assuming that the pollutants were well mixed within the PBL, and the emission rate of each pollutant was then summed from the above six emission sectors. The primary emissions from anthropogenic activities and biogenic sources were set to zero when the trajectory was above the PBL, and biomass burning emissions were assumed to be well mixed within 3,000 m.

Both single backward trajectories and clusters were obtained using the HYSPLIT model (v4.9; Draxler et al., 2018). In this study, a total of 103 3-D 3-day backward trajectories were computed once per day at the

time when hourly $O_3$ peak was observed on selected $O_3$ episode days (defined as when MDA8 $O_3$ exceeded 75 ppbv) during April–September 2018 with an ending point at an altitude of 300 m above ground level over Mount Tai. Four principal air mass clusters were determined using a built-in cluster analysis tool within the HYSPLIT model, and represented by their average transport trajectory. A detailed description of these four air mass clusters will be given in Section 3.2. The meteorological data used to drive the HYSPLIT model were provided by the Global Data Assimilation System (0.5°). Real-time meteorological parameters (temperature and RH) for the single backward trajectories were obtained along with the 103 backward trajectories, while for trajectory clusters meteorological parameters were obtained as averages of single backward trajectories included in each cluster.

The model only considered the emissions, photochemistry and transport of air pollutants in the regions fixed by the individual 3-day backward trajectories, while the processes outside these regions were not considered explicitly and only approximated by the initial concentrations of various pollutants in the model. As an air parcel traveled along a pre-defined trajectory, the initial concentrations of major pollutants were determined as follows. When the trajectory was below the PBL, $O_3$, $NO_2$, CO, and $SO_2$ were first initialized using the observational data obtained from the sites in the China's National Environmental Monitoring Center (CNEMC) Network, which are located nearest to the origin areas, and NO and NMVOCs were initialized using the data obtained from a typical urban site (Sun et al., 2018). When the trajectory was above the PBL, the initial concentrations of major pollutants were constrained using the regional background concentrations. For NMVOCs, the regional background concentrations were set using the data obtained from Mount Tai (Zhu et al., 2017). For other pollutants, the regional background concentrations in the NCP were determined using the observational data at Mount Tai, and those in other regions were obtained from previous studies (Wang, Xu, et al., 2017; Xing et al., 2017; Xu et al., 2020). Model simulations were then iteratively performed according to (E1) to make the model-simulated $O_3$ and related species be more reasonably consistent with the in-situ measurement data at Mount Tai:

$$CI_{i+1} = CI_i * \left(C_{\text{obs}} / CE_i\right) \quad \text{(E1)}$$

where $CI_i$ and $CE_i$ represent the initial and final concentrations of the target pollutant in the $i^{th}$ simulation, respectively, and $C_{\text{obs}}$ refers to the observed concentration of the target pollutant. Meteorological parameters, including temperature and RH, were initialized using the data obtained along with the backward trajectories. The maximum and minimum PBL heights obtained with the backward trajectories were also input into the model to calculate the real-time PBL heights.

For the model simulations, the meteorological parameters (temperature and RH) and emissions rates of major pollutants were read in with a time resolution of 1 h. These pollutants were then subjected to complex chemical reactions and physical processes. From the base model runs, we quantified the contributions from different source regions to the regional $O_3$ concentrations observed at Mount Tai on the 103 $O_3$ episode days during April–September 2018. In addition to the base runs, a series of sensitivity experiments were carried out to diagnose the formation regimes of the regional $O_3$ based on three classified major trajectory clusters, as described in Section 3.3. There were three major $O_3$ precursor groups, including NOx, anthropogenic hydrocarbons (AHC), and biogenic hydrocarbons (BHC). The AHC group was further sub-divided into low-reactivity hydrocarbons (LRHC, including ethane, propane, acetylene, and benzene), alkanes with carbon numbers ≥4 (C4HC), alkenes, and reactive aromatics (AROM; comprising most aromatics except for benzene). The detailed NMVOCs categorization is provided in Table S1.

## 3. Results and Discussion

### 3.1. $O_3$ Pollution Overview in 2018 and Comparison with 2006–2009

Figure 1 depicts the seasonal variations of surface $O_3$ at Mount Tai derived from the 1-year continuous observations in 2018. Overall, the $O_3$ exhibited a unimodal seasonality with a peak in June (85 ± 21 ppbv) and minimum in December (30 ± 8 ppbv). Further inspection shows that $O_3$ concentrations steadily increased from January to June and unevenly decreased from June to December. Specifically, $O_3$ concentrations were nearly constant in July–September and then sharply decreased from September to December. The factors

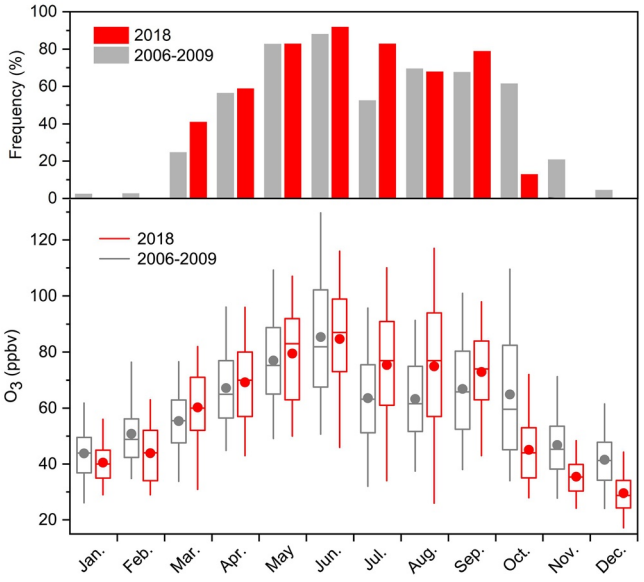


**Figure 1.** Seasonal variations of surface $O_3$ mixing ratios at Mount Tai during 2006–2009 and 2018. The box plot provides the 5%, 25%, 50%, 75% and 95% the data, while the dots indicate the average mixing ratios. The upper panel shows the frequency of the non-attainment days when MDA8 $O_3$ exceeded the Chinese National Ambient Air Quality Standard, that is, 75 ppbv (Class II). The previous data in 2006–2009 have been reported in Sun et al. (2016).

that shaped such a seasonal pattern of $O_3$ concentrations are elucidated as follows. The steadily increasing $O_3$ concentrations from January to June were affected by increasing temperatures and stronger photochemical activity, and the sharply decreasing $O_3$ concentrations from September to December were affected by decreasing temperatures and weakened photochemical activity. The frequent occurrence of stratosphere-to-troposphere exchange in April–May (as indicated by the observed high $O_3$ with low CO and RH in some cases) and strong biomass burning intensity in June also partly explain the high regional $O_3$ concentrations in these months (Chen et al., 2017; Tarasick et al., 2019). From June to July–August, the sharply decreasing $O_3$ concentrations were mainly due to the influence of strengthened Asia summer monsoon which decreased the intensity and frequency of stable anti-cyclonic synoptic weather circulation and brought more precipitation as indicated by the frequent cloudy days in July and August in Figure S1 (Ma et al., 2019; Zhang et al., 2016). The upper panel of Figure 1 shows the frequency of the $O_3$ episode days with MDA8 $O_3 \geq 75$ ppbv. Despite the high elevation and remote location, MDA8 $O_3$ non-attainment (exceedance) episodes occurred quite frequently at Mount Tai in the warm seasons, that is, April–September (59%–92% of days). In comparison, few non-attainment days were encountered in the cold seasons (October–March, 0%–41%). Hereafter, we focused on tracking the $O_3$ pollution sources in April–September.

Figure 2 presents the average diurnal variations of $O_3$, related species, and meteorological parameters in the warm and cold seasons. During both periods, major trace gases ($O_3$, NO, $NO_2$, NOy, and CO) showed well-defined diurnal cycles with a broad daytime concentration peak, which can be explained by the combined influence of PBL evolution, mountain–valley breeze, and atmospheric photochemistry (for $O_3$). The exact peak time

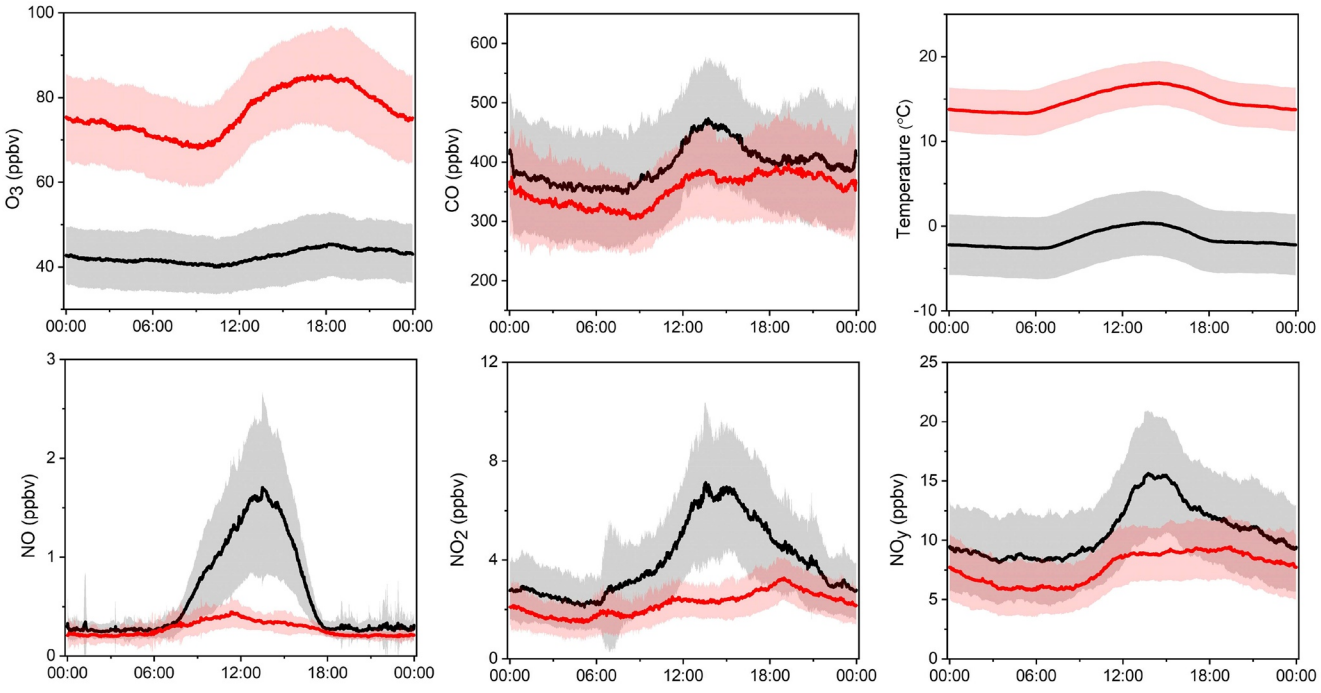


**Figure 2.** Average diurnal variations of $O_3$, related species, and meteorological parameters at Mount Tai during April–September (warm season; red) and October-March (cold season; black) 2018. Error bars indicate half standard deviation of the mean.

varied from pollutant to pollutant due to their different lifetimes and photochemical behaviors. Primary pollutants such as NO, $NO_2$, and CO exhibited higher concentrations in the cold seasons, whereas $O_3$ concentrations and ambient temperatures were substantially higher in the warm seasons. Two points are noteworthy here. First, higher regional background $O_3$ concentrations (calculated as the average value between 02:00 and 05:00 LT) were observed in the warm seasons (73 ± 20 ppbv) than in the cold seasons (42 ± 14 ppbv). Here we use the $O_3$ data during the hours of 2:00–5:00 LT to indicate regional background $O_3$ concentrations for two reasons, on one hand, Mount Tai is in the nocturnal residual layer and no local photochemistry occurs at nighttime, on the other hand, the NO titration effect was relatively weak during 2:00–5:00 LT (inferred from the diurnal variations of $NO_2$). Second, there was a larger enhancement (defined as the maximum minus the minimum) of the diurnal $O_3$ cycle in the warm seasons (38 ± 16 ppbv) than in the cold seasons (17 ± 8 ppbv), which indicates stronger photochemical ozone production in the warm seasons. These two factors together are responsible for the frequent MDA8 $O_3$ exceedance episodes in the warm seasons at Mount Tai.

The measurement results in 2018 and 2006–2009 are compared to demonstrate the decadal change of the regional $O_3$ concentrations (Figure 1), and one-way analysis of variance method (one-way ANOVA) was used to test the significance of the change. Compared with 2006–2009, the $O_3$ concentrations in 2018 were higher in the warm seasons (excluding June; $p < 0.01$) and lower in the cold seasons (excluding March; $p < 0.01$). The change in the warm-season $O_3$ is generally consistent with the increasing long-term $O_3$ trend (Li, Jacob, et al., 2019; Lu et al., 2018, 2020; Sun et al., 2016; Xu et al., 2020). We further selected July–October to examine the reasons responsible for such inter-annual variations considering both the severe $O_3$ pollution and large changes in $O_3$ concentrations during this period. For the meteorological parameters, higher temperatures and fewer cloudy days favored $O_3$ formation. We found that ambient temperature modestly increased in July (by 1.2 °C; $p < 0.01$) and August (by 1.7 °C; $p < 0.01$), slightly decreased in September (by −0.2°C; $p = 0.13$), and significantly decreased in October (by −2.5°C; $p < 0.01$) in 2018 compared with 2006–2009 (Figure S2). The significance of inter-annual variations of temperature was tested by one-way ANOVA. Cloudy days (i.e., with RH ≥ 95%) increased in July (by 17%), August (by 7%), and September (by 6%), but decreased in October (by −12%) (Figure S1). The temperature variations may partly explain the $O_3$ inter-annual variations in July, August, and October.

We selected a large regional domain scale (33–38°E, 115–120°N) to track the variations in abundance of the $O_3$ precursors based on the satellite retrievals (Figure S3). The data of tropospheric $NO_2$ column and vertical HCHO column were retrieved from the Ozone Monitoring Instrument (OMI; https://disc.gsfc.nasa.gov/. DOI:10.5067/Aura/OMI/DATA3007; DOI:10.5067/Aura/OMI/DATA3010). The amount of the tropospheric $NO_2$ column showed a significant decrease in July–September (by −10%, −30%, and −20%, respectively; $p < 0.01$) but showed an increase in October (by 14%; $p < 0.01$) in 2018 compared with 2006–2009. In contrast, the amount of the vertical HCHO column showed a significant increase in July–September (by 25%, 38%, and 17%, respectively; $p < 0.01$) and leveled off in October. The significance of inter-annual variations in the amount of tropospheric $NO_2$ column and vertical HCHO column was tested by one-way ANOVA. The consistent inter-annual variations of $O_3$ and HCHO abundance in July–September suggest that increasing VOCs is an important factor that enhances regional $O_3$ concentrations (Sun et al., 2016, 2019). We also examined the variations of other related factors. For example, the intensity of biomass burning activity declined in October, as indicated by a decrease in the number of fire spots within the selected domain scale (Figure S4). Overall, from 2006–2009 to 2018, the significant regional $O_3$ increase in July–September can be attributed to the elevated temperatures and increasing VOCs, and the sharp regional $O_3$ decrease in October can be attributed to the lower temperatures and weakened biomass burning intensity. Further observations are required to establish the long-term $O_3$ trends under the rapidly changing environment and climate in the NCP region.

### 3.2. Source Apportionment of $O_3$ Pollution

To identify the origins and transport patterns of the captured air masses, the three-dimensional 3-day backward trajectories for the 103 $O_3$ episode days were classified into four groups using a built-in cluster analysis tool within the HYSPLIT model. Figure 3 shows the four principal air mass clusters superimposed on the anthropogenic NMVOCs emissions. In the figure, "NEC" refers to the air masses from the north traveling over northeastern China; "EC" refers to the air masses from the southeast traveling over eastern China

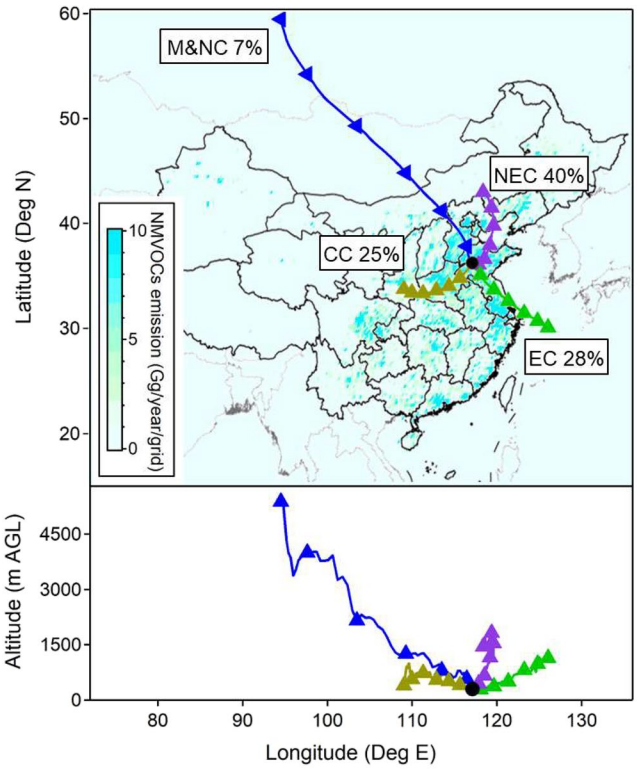


**Figure 3.** Principal air mass types and the 3-day backward trajectories arriving at Mount Tai during the 103 $O_3$ episodes in April-September 2018. The emission data of non-methane VOCs were taken from Li et al. (2017). Four principal air masses: (1) NEC: Northeast China, (2) EC: East China, (3) CC: Central China, and (4) M&NC: Mongolia and North China.

at low altitudes; "CC" refers to the air masses from the southwest traveling slowly over central China at low altitudes; and "M&NC" refers to the air masses from the northwest traveling quickly over Mongolia and northern China at relatively high altitudes. During the $O_3$ episodes in April–September, the NEC air mass occurred most frequently with a fraction of 40%, followed by EC (28%), CC (25%), and M&NC (7%); however, the dominant air masses varied between the different months (Table 1). The most frequent air mass was CC (56%) in April, which then changed to NEC (54%) in May. In June, NEC and EC were comparably frequent (35%), which then switched to EC (64%) in July. In August and September, the most frequent air mass again changed to NEC (67% and 55%, respectively). We also compared the summer transport pattern in 2018 with that in 2003–2015, and found that the EC air mass dominated in the summer during both periods. Such patterns in air mass transport are mainly attributed to the evolution of the Asian monsoon (Ding et al., 2008).

To further locate the origins of the $O_3$ precursors affecting Mount Tai, we present the spatial distributions of the NOx and NMVOC emission intensities along the 103 backward trajectories in Figure 4. The emission intensity of NOx and NMVOCs was calculated as the sum of the overall emission rate (Section 2.2) of the individual species. From a spatial perspective, there was a strong emission intensity within the NCP for both NOx and NMVOCs, which is consistent with previous studies that showed high NOx and NMVOC concentrations over the NCP (Li, Zhang, et al., 2019; Liu & Wang, 2020). This indicates that the $O_3$ pollution at Mount Tai was mainly influenced by $O_3$ precursor emissions in the NCP region. Few emissions were injected into the LPTM model outside of the NCP (with an exception of the Yangtze River Delta (YRD) in June–August) because most air masses moved at higher altitudes prior to approaching the NCP. On a temporal scale, the origins of the NOx and NMVOC emissions varied from month to month, which corresponds to the different dominant air masses. For example, NOx and NMVOCs were mainly from the southwestern part of the NCP in April, from the southeastern part of the NCP in June and July, and from the northern part of the NCP in May, August, and September (Figures S5 and S6). Overall, the NCP region was confirmed to be the major origin of the O3 precursors affecting Mount Tai.

Figure 5 compares the $O_3$, Ox, NOx, and CO results of the observations and LPTM simulations for the selected 103 $O_3$ episodes in April–September. The statistical measures used to evaluate the LPTM performance are documented in Table S2. The LPTM simulations showed generally reasonable agreement with the observations for most of the pollutants, as indicated by both the strong correlations ($R^2$: 0.41–0.81) and the reduced major axis (RMA) slopes (0.88–1.25). The results of statistical evaluation further confirmed the good performance of the LPTM, with mean fractional bias (MFB) and mean fractional error (MFE) meeting the benchmarks (MFB: 15%; MFE: 35%) recommended by the USEPA (2007). The model validation demonstrates that the LPTM is capable of reproducing the observations, which reflects a good representation of the emissions, chemistry, and physical processes. The good agreement also verifies the accuracy of the identified origins of the $O_3$ precursors, and provides a suitable method for quantifying the contributions of different source regions to the regional $O_3$ concentrations.

**Table 1**
*Frequency of Major Air Mass Types Arriving at Mount Tai During the $O_3$ Episodes in April–September 2018*

| Type | April | May | June | July | August | September | April-September |
|---|---|---|---|---|---|---|---|
| NEC | 25% | 54% | 35% | 8% | 67% | 55% | 40% |
| EC | 0% | 13% | 35% | 64% | 33% | 13.5% | 28% |
| CC | 56% | 29% | 30% | 28% | 0% | 13.5% | 25% |
| M&NC | 19% | 4% | 0% | 0% | 0% | 18% | 7% |

The contributions of the NCP and regions outside of the NCP to the regional $O_3$ concentrations observed at Mount Tai during the $O_3$ episodes in April–September were quantified based on the regional $O_3$ formation potential (ROFP). For a traveling aged air mass, the ROFP over a specific area is calculated by:

$$\mathrm{ROFP} = O_{3\mathrm{MAX}} - O_{3\mathrm{MIN}} \quad \text{(E2)}$$

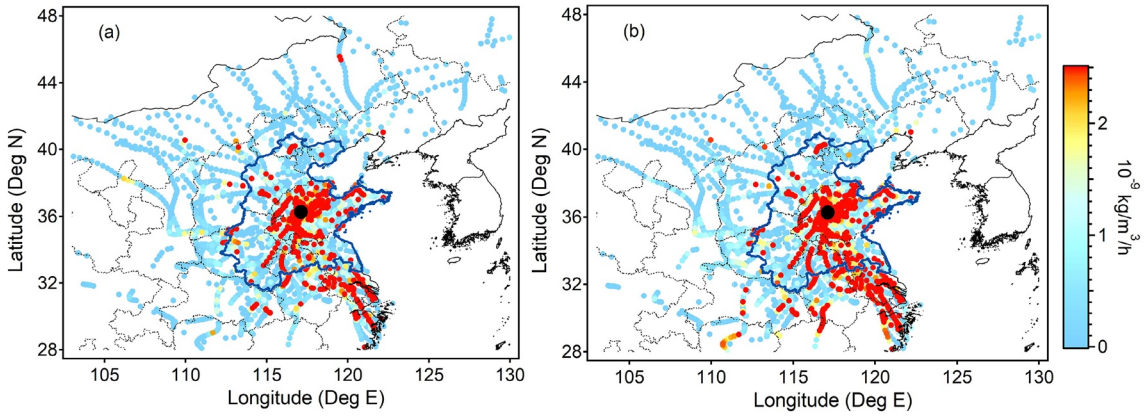


**Figure 4.** Spatial distributions of the (a) NOx and (b) NMVOC emission intensities along the 3-day backward trajectories arriving at Mount Tai during the $O_3$ episodes in April–September 2018. The areas inside the blue line refer to the domain of NCP region defined in this study.

where $O_{3MAX}$ refers to the LPTM-simulated maximum hourly $O_3$ concentration on the last day (to guarantee that $O_3$ precursors have sufficiently undergone photochemical reactions) in the receptor area, and $O_{3MIN}$ refers to the selected LPTM-simulated hourly minimum $O_3$ concentration that appeared prior to the $O_{3MAX}$ in the receptor area. Such calculations reduce the uncertainties introduced by $O_3$ diurnal variations and can fully characterize the ongoing photochemical reactions over different source regions. As shown in Figure 6, the NCP was identified as a major source region to the LPTM-simulated regional $O_3$ concentrations

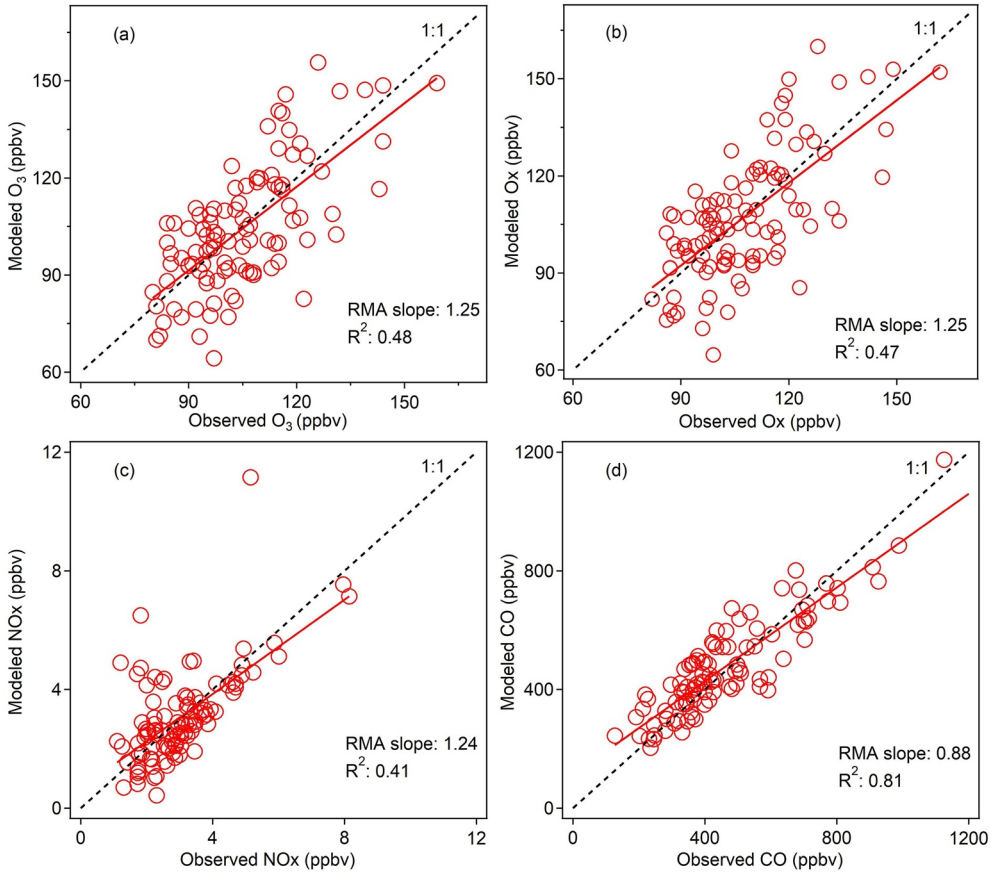


**Figure 5.** Comparison of (a) $O_3$, (b) Ox, (c) NOx, and (d) CO between field observations and LPTM simulations for the 103 $O_3$ episodes in April–September 2018. LPTM, Lagrangian photochemical trajectory model.

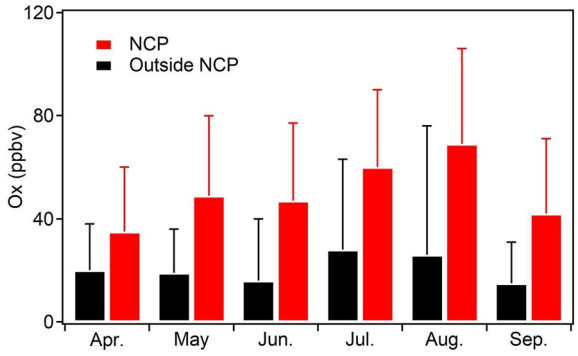


**Figure 6.** Contributions (calculated based on Regional $O_3$ Formation Potential [ROFP]) of NCP and regions outside NCP to the LPTM-simulated $O_X$ concentrations at Mount Tai during the $O_3$ episodes in April-September 2018. Error bars indicate standard deviation of the mean. LPTM, Lagrangian photochemical trajectory model; NCP, North China Plain.

with an average contribution of 74% ± 27%, which further confirms that $O_3$ pollution observed at Mount Tai is regionally representative. The Ox ($Ox = O_3 + NO_2$) data were used in the calculations to eliminate the effect of NO titration. A notable point of these results is the high simulated $O_3$ concentrations in July and August. On one hand, this finding reveals rapid $O_3$ production in July and August due to high temperatures and abundant precursors. On the other hand, the high simulated $O_3$ concentrations in these two months should be related to the LPTM's overestimation due to the lack of rain deposition in the model. Corresponding to the NOx and NMVOCs emission origins, the regional $O_3$ concentrations were mainly contributed by the southwestern part of the NCP in April, by the southeastern part of the NCP in June and July, and by the northern part of the NCP in May, August, and September.

### 3.3. Sensitivity of Regional $O_3$ Pollution to Coordinated Reduction of $O_3$ Precursors

We examined the formation regimes of regional $O_3$ for the major air mass clusters NEC, EC, and CC based on a metric of relative incremental reactivity (RIR) (M&NC was not considered due to the low frequency and high elevation). RIR is defined here as the ratio of the percent decrease in the LPTM-simulated regional $O_3$ concentrations to the percent decrease in the emissions of the target $O_3$ precursor group over a specific source region. Figure 7 shows the RIRs for the different $O_3$ precursor groups in designated regions: "Local" refers to Ji'nan and Tai'an (the closest cities surrounding Mount Tai); "NCP" refers to the other areas over the NCP (Figure 4) excluding Ji'nan and Tai'an; and "Outside NCP" refers to areas excluding Local and NCP. Overall, the regional $O_3$ formation was most sensitive to emission reductions over the NCP for all three air mass clusters, which is consistent with the source apportionment results in Section 3.2. We therefore focused on the emission reductions in the NCP region in the following analyses.

As shown in Figure 7, the key precursors varied among the three major air mass clusters as they traveled over different areas and thus have different NOx and NMVOC emission characteristics. For air masses traveling over the northern part of the NCP (i.e., NEC), regional $O_3$ formation was highly sensitive to AHC,

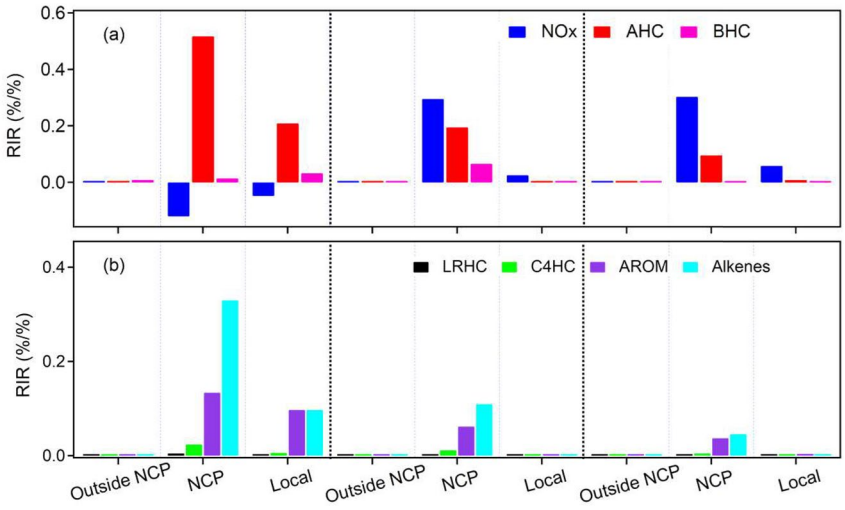


**Figure 7.** The LPTM-calculated RIRs for (a) major $O_3$ precursor groups and (b) the AHC sub-groups over different source regions among major air mass clusters. The left, middle, and right panel divided by the black dotted line was for major air mass types NEC, EC, and CC, respectively. Three major source regions: (1) Local: Tai'an and Ji'nan, (2) NCP: The areas covered in the blue line in Figure 4 excluding Tai'an and Ji'nan, (3) Outside NCP: The areas excluding Local and NCP. Refer to Table S1 for the detailed speciation of LRHC, C4HC, AROM, and alkenes. LPTM, Lagrangian photochemical trajectory model; NCP, North China Plain; RIR, relative incremental reactivity.

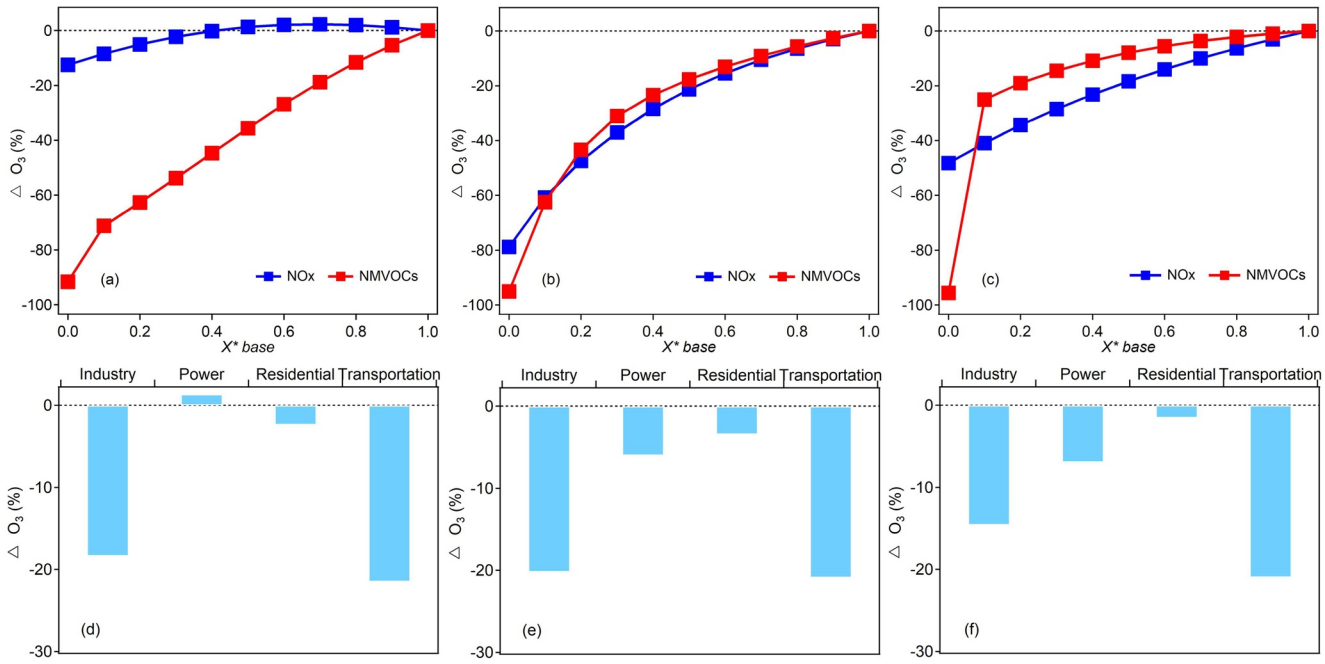


**Figure 8.** The LPTM-simulated regional $O_3$ change (a–c) as a function of the X times of the base emission intensity of $NO_2$ and NMVOCs and (d–f) as a result of shutting off major emission sectors over the NCP region. The left, middle, and right panel was for major air mass types NEC, EC, and CC, respectively. LPTM, Lagrangian photochemical trajectory model; NCP, North China Plain.

which was dominated by alkenes followed by reactive aromatics (Figure 7b). The RIRs for NOx were negative. Examination of detailed air mass trajectory and the associated anthropogenic emissions revealed that the NEC air masses had traveled in a highly polluted region with more intense NOx emissions prior to arriving at Mt. Tai. Thus, the NEC air masses contained higher levels of NOx compared to the EC and CC air masses and the $O_3$ formation was in a NOx-saturated regime during the transport over the NCP region. A small amount of NOx reduction would lead to less NO titration and higher regional $O_3$ concentrations. We further examined the effects of precursor reduction with different ratios over the NCP on regional $O_3$ concentrations (Figure 8a) and found that the control of NOx emissions only contributed to a regional decrease of $O_3$ when the reduction ratios exceeded 50%. Along similar reduction scales, the control of NMVOCs was consistently and significantly superior to NOx control for improving the regional $O_3$ pollution. Figure 8b shows the effects of shutting off major emission sectors over the NCP on the regional $O_3$ concentrations. For the NEC air mass, control priority should be given to the transportation and industry emission sectors, which reduced the regional $O_3$ concentrations by −22% and −18%, respectively, whereas the control of residential emissions showed little impact (−2%). In fact, shutting off the power sector alone even caused a slight increase (1%) in regional $O_3$ concentrations due to the high NOx emissions.

For air masses traveling over the southern part of the NCP (i.e., EC and CC), regional $O_3$ formation was most sensitive to NOx and to a lesser extent AHC (alkenes and reactive aromatics are key compounds) at 10% reductions. However, when shutting off the primary emissions over the NCP (i.e., 100% reductions), regional $O_3$ formation showed a larger dependence on AHC. The turnover was caused by the substantially slower radical cycling with 100% NMVOC reductions, which further affected NOx cycling and significantly limited $O_3$ formation. BHC showed relatively higher RIR (0.07) in the EC than in the NEC (0.01) and CC (0.001). Similar to the NEC results, controlling transportation and industry emissions would significantly reduce regional $O_3$ concentrations (by −21% and −20% for EC, respectively, and by −21% and −15% for CC), whereas controlling residential emissions showed little impact (reductions by −3% for EC and −2% for CC). The effect of shutting off power emissions resulted in a modest decrease (by −6% for EC and −7% for CC) of the regional $O_3$ concentrations. These results elucidate the different $O_3$ formation regimes among the three major air mass clusters and provide detailed information on the $O_3$-precursor relationships along the regional transport of aged air masses to Mount Tai.

Previous studies have reported the significant impacts of biomass burning on regional air quality over the NCP in June, the winter-wheat harvest season in northern China (Chen et al., 2017; Gu et al., 2020). In this study, we focused on the impact of biomass burning on regional $O_3$ concentrations. To elucidate the impact, we selected three typical cases with 3-day backward trajectories that had traveled over areas with intense fire spots and been injected into comparatively large biomass burning emissions, as shown in Figures S7 and S8. The 3-day backward trajectories of cases (a) and (b) came from eastern China and were classified into type EC. For case (a)/(b), the observed maximum $O_3$ concentrations were 113/114 ppbv, and the simultaneously observed concentrations of NOx and CO were 3.25/2.05 ppbv and 433/376 ppbv, respectively. Shutting off biomass burning emissions caused an −8% and −5% decrease in the LPTM–simulated regional $O_3$ concentrations over the receptor site. For case (c), the 3-day backward trajectory came from northeastern China and was classified into type NEC. The observed maximum concentration of $O_3$ (98 ppbv) and simultaneously observed concentration of CO (356 ppbv) were lower than the former two cases, but the simultaneously observed NOx concentrations (4.70 ppbv) were higher. Shutting off biomass burning emissions caused an −11% decrease in the LPTM–simulated regional $O_3$ concentrations over the receptor site. Further inspection of the time series (Figure S7) and 3-day backward trajectories (Figure S8) clearly showed that the decreased regional $O_3$ concentrations in these three cases were mainly caused by reduced biomass burning emissions from the NCP. These results suggest that biomass burning remains an important emission source over the NCP under certain circumstances and should be given attention in future control measures.

Jian and Fu (2014) showed that the retrieved smoke pixel heights ranged from 0 to 6 km above the local terrain over peninsular Southeast Asia, and 55% of the smoke pixels were below 1 km. Here we chose a median value of 3 km as biomass-burning smoke plume height (named as "BASE" scenarios) and conducted a series of sensitivity tests in June by assuming that biomass burning emissions were well mixed within 1 km (named as "ADJ" scenarios). The uncertainties introduced by biomass burning emission treatment were evaluated from three aspects. First, there is a negligible impact on the change in LPTM-simulated $O_3$ mixing ratios for the 17 $O_3$ episodes in June (<3%; $R^2 = 0.81$); Second, the NCP was identified as a dominant source region to the LPTM-simulated regional $O_3$ concentrations under both scenarios (with an average contribution of 74% and 78% under "BASE" and "ADJ" scenarios, respectively); Third, under "ADJ" scenarios, shutting down the biomass burning emissions resulted in decreases of −13%, −9%, and −18% in the LPTM–simulated regional $O_3$ concentrations over the receptor site for case (a), (b), and (c), respectively. Overall, the results indicated that the impacts of model treatment of biomass burning emissions on major conclusions should be minor.

### 3.4. Implications for Control Policy

Surface $O_3$ pollution over the NCP in summer is among the most severe worldwide, as indicated by studies within the Tropospheric Ozone Assessment Report (Cooper et al., 2020; Fleming et al., 2018; Gaudel et al., 2018; Lefohn et al., 2018; Xu et al., 2020). The long-term increasing trend of surface $O_3$ concentrations and regional background $O_3$ concentrations implies a worsening prospect of regional $O_3$ pollution, as well as the strong interplay between them (Sun et al., 2016; Xu et al., 2020). In Sections 3.2 and 3.3, we showed the significant impacts of ground-level emissions to high-elevation $O_3$ concentrations. In this section, we focus on the implications of high-elevation $O_3$ on ground-level $O_3$ pollution. Previous studies have reported that the downward transport of high-elevation $O_3$ would aggravate ground-level $O_3$ pollution to a certain degree (Zhu et al., 2020). Here we used the nocturnal averages of ambient $O_3$ concentrations (between 02:00 and 05:00 LT) observed at Mount Tai to represent regional background $O_3$ concentrations, and further examined to what spatial scales the regional background $O_3$ observed at Mount Tai can offer accurate indications for the next day's ground-level $O_3$ pollution.

We calculated the MDA8 $O_3$ concentrations of 24 selected cities (Figure S9) around Mount Tai and performed correlation analyses with the regional background $O_3$ observed at Mount Tai (Figure 9a). The 24 selected cities cover most areas of the NCP, and all (excluding Tai'an) are identified as key cities of the air pollution transport channel in Jing-Jin-Ji (a total of 28 cities whose air pollution have high potential to affect the air quality in Beijing and the whole Jing-Jin-Ji region; http://www.mee.gov.cn/). The MDA8 $O_3$ of the individual cities was calculated using the MDA8 $O_3$ averages of all of sites in the CNEMC inside each city. There were significant positive correlations between the regional background $O_3$ and ground-level

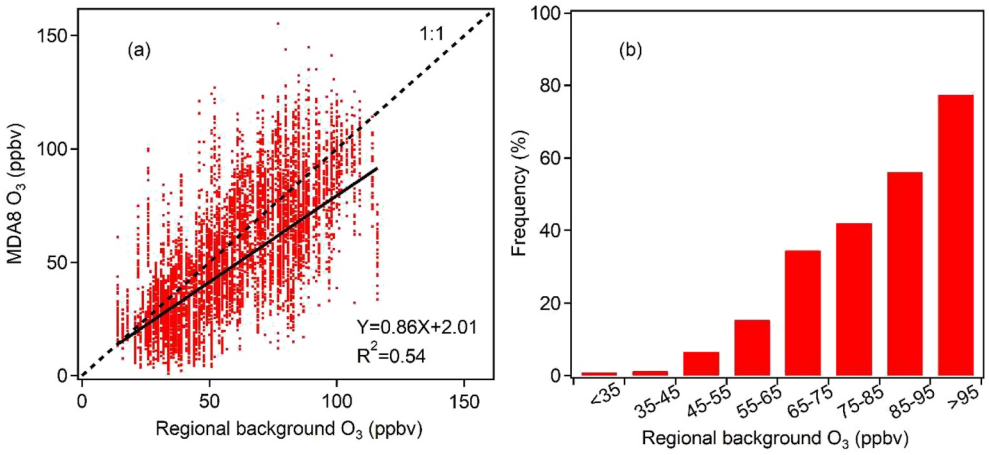


**Figure 9.** (a) Scatter plots of the MDA8 $O_3$ concentrations in 24 surrounding cities (see the detailed information in Figure S9) versus nocturnal regional background $O_3$ concentrations observed at Mount Tai; (b) The frequency of the non-attainment days when MDA8 $O_3$ of 24 surrounding cities exceeded the Chinese National Ambient Air Quality Standard (i.e., 75 ppbv [Class II]) versus different ranges of regional background $O_3$ concentrations. Regional background $O_3$ concentrations were obtained using the ambient $O_3$ averages observed at Mount Tai between 02:00 and 05:00 LT. The MDA8 $O_3$ of the individual cities was calculated using the MDA8 $O_3$ averages of all of sites in the China's National Environmental Monitoring Center (CNEMC) Network inside each city.

MDA8 $O_3$ ($R^2$: 0.54; slope: 0.86). The detailed correlation analysis results of individual cities are presented in Figure S10. There was a decreasing slope tendency (ranging from 0.99 to 0.76) and $R^2$ (ranging from 0.65 to 0.44) with increasing distance from Mount Tai, and the largest slope and $R^2$ were found in Ji'nan and Tai'an, respectively, which are the closest cities to Mount Tai. We also calculated the MDA8 $O_3$ non-attainment frequency of all 24 cities corresponding to the different ranges of regional background $O_3$ (Figure 9b). The MDA8 $O_3$ non-attainment frequency increased steadily with increasing regional background $O_3$. When the regional background $O_3$ concentration was less than 35 ppbv, the MDA8 $O_3$ non-attainment frequency was small (<1% of days), but when it exceeded 55 ppbv, the MDA8 $O_3$ non-attainment frequency of the 24 surrounding cities rapidly increased (by 16% ± 6% on average for each 10-ppbv increase of regional background $O_3$ concentrations ranging from 55 to 95 ppbv), and the MDA8 $O_3$ non-attainment frequency of the 24 surrounding cities exceeded 50% when the regional background $O_3$ concentration was higher than 85 ppbv. There was also a decreasing tendency of the MDA8 $O_3$ non-attainment frequency with increasing distance from Mount Tai (Figure S10). These results suggest that regional background $O_3$ is a good indicator for forecasting ground-level $O_3$ pollution over a relatively large spatial scale. For comparison, we performed similar analyses but used the $O_3$ data observed at Mount Tai during 0:00–5:00 and 0:00–6:00 LT to represent regional background $O_3$ concentrations, and the results showed little impacts on our major conclusions.

In this study, we traced the sources of regional $O_3$ pollution over the NCP based on data observed at the summit of Mount Tai, examined the sensitivity of regional $O_3$ pollution to coordinated precursor reduction, and further revealed the satisfactory ability of regional background $O_3$ to indicate ground-level $O_3$ pollution. Based on these results, we provide the following suggestions for future control of surface $O_3$ pollution. First, nocturnal $O_3$ observed at Mount Tai is a good indicator for ground-level $O_3$ pollution over a wide spatial coverage. Second, the NCP itself serves as the major source region for both precursor and regional $O_3$ concentrations. Improving the severe surface $O_3$ pollution would require synchronous reductions of regionally emitted precursors. Lastly, we suggest that different emission reduction measures should be implemented over different domains to better control surface $O_3$ pollution. Specifically, the northern part of the NCP should reduce NMVOC emissions while the southern part of the NCP should place emphasis on NOx reductions. From the perspective of specific emission sectors, control policy should give priority to the transportation and industry emission sectors.

## 4. Conclusions

We analyzed the year-round $O_3$ observations obtained at Mount Tai, northern China, in 2018. The frequent occurrence of MDA8 $O_3$ non-attainment episodes (59%–92% of days) revealed the severe regional $O_3$ pollution in the NCP region in the warm seasons. Well-defined diurnal cycles of major trace gases with a broad daytime concentration peak elucidated the important contributions of regional transport. From 2006–2009 to 2018, $O_3$ concentrations showed a significant enhancement in July–September due to elevated temperatures and increasing VOCs, but sharply declined in October due to lower temperatures and weakened biomass burning intensity. The magnitude and pattern of observed $O_3$ and related trace gases were well reproduced by the Lagrangian photochemical trajectory model. Further inspection of the model results suggested that the NCP is responsible for both the precursors and high regional $O_3$ concentrations (with an average contribution of 74% ± 27%) observed at Mount Tai during the $O_3$ episodes in April–September. Regional $O_3$ formation was highly NOx-sensitive in air masses traveling from the southern part of the NCP and AHC-sensitive in air masses from the northern part of the NCP. Key species within the AHC group were alkenes followed by aromatics. Control policy should give priority to the transportation and industry emission sectors considering their significance to reducing regional $O_3$ concentrations. Biomass burning was also found to make an important contribution to regional $O_3$ concentrations under certain circumstances. This study reveals that the regional background $O_3$ observed at the studied mountaintop provides a good indication of the surface $O_3$ pollution over a wide spatial coverage, and provides scientific support for the formulation of regional collaborative control policies to mitigate photochemical air pollution in the NCP region.

Although the efficacy of the LPTM has been confirmed by the reasonable agreement between model simulations and field observations, it is indeed subject to some uncertainties, mainly because of the lack of more refined trajectories and emission inventories as well as the relatively coarse spatial resolutions of the model. More efforts are still required to further enhance the LPTM's performance. The following directions are recommended for the future study: (1) the air mass trajectory with higher spatial resolutions is in great demand to better resolve the regional transport from upwind areas and local dynamics around the receptor area; (2) weather conditions such as cloud fraction and rainy days over traveling areas would significantly influence photolysis rate of pollutants, therefore, parameterizations of these processes in the model are of great importance; and (3) the emission inventories with higher temporal and spatial resolutions and detailed NMVOC emission profile are highly needed to reduce the uncertainty related to primary emissions.

**Acknowledgments**
We thank the University of Leeds for providing the Master Chemical Mechanism (version 3.3.1), the NOAA Air Resources Laboratory for providing the HYSPLIT model, and the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) for the free distribution of the OMI satellite data through the website (https://disc.gsfc.nasa.gov/). We also thank the Tsinghua University for providing the MEIC emission inventory, and the University of California, Irvine for providing the biogenic emission inventory. This work was funded by the National Natural Science Foundation of China (41922051), Shandong Provincial Science Foundation for Distinguished Young Scholars (ZR2019JQ09), National Key Research and Development Program of China (2016YFC0200500), and the Jiangsu Collaborative Innovation Center for Climate Change. We appreciate the two anonymous reviewers for their helpful suggestions to improve the original manuscript.

## Data Availability Statement

Data associated with this study are accessible at http://dx.doi.org/10.17632/hjkbkkktsc.1.

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