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Recommendations on benchmarks for chemical transport model applications in China – Part 2: Ozone and Uncertainty Analysis

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Abstract

Ground-level ozone (O_3) has emerged as a significant air pollutant in China, attracting increasing attention from both the scientific community and policymakers. Chemical transport models (CTM) serve as crucial tools in addressing O_3 pollution, with frequent applications in predicting O_3 concentrations, identifying source contributions, and formulating effective control strategies. The accuracy and reliability of the simulated O_3 concentrations are typically assessed through model performance evaluation (MPE). However, the wide array of CTMs available, variations in input data, model setups, and other factors result in a broad range of simulated O_3 concentration differences from observed values, highlighting the necessity for standardized benchmarks in O_3 evaluation.

Built upon our previous work, this study conducted a thorough literature review of CTM applications simulating O_3 in China from 2006 to 2021. 216 relevant articles out of a total of 667 reviewed were identified to extract quantitative MPE results and key model configurations. From our analysis, two sets of benchmark values for six commonly used MPE metrics are proposed for CTM applications in China, categorized into "goal" benchmarks representing optimal model performance and "criteria" benchmarks representing achievable model performance across a majority of studies. It is recommended that the normalized mean bias (NMB) for hourly O_3 and daily 8-hr maximum O_3 concentrations should ideally fall within ±15% and ±10%, respectively, to meet the "goal" benchmark. If the "criteria" benchmarks are to be met, the NMB should be within ±30% and ±20%, respectively. Moreover, uncertainties in O_3 predictions due to uncertainties in various model inputs were quantified using the decoupled direct method (DDM) in a commonly used CTM. For the simulation period of June 2021, the total uncertainty of simulated O_3 ranged 4-25 $\mu g/m^3$, with anthropogenic volatile organic compound (AVOC) emissions contributing most to the uncertainty of O_3 in coastal regions and O_3 boundary conditions playing a dominant role in the northwest region. The proposed benchmarks for assessing simulated O_3 concentrations, in conjunction with our previous studies on $PM_{2.5}$ and other criteria air pollutants, represent a comprehensive and systematic effort to establish a model performance framework for CTM applications in China. These benchmarks aim to support the growing modeling community in China by offering a robust set of evaluation metrics and establishing a consistent evaluation methodology relative to the body of prior research, thereby helping to establish the credibility and reliability of their CTM applications. These statistical benchmarks need to be periodically updated as models advance and better inputs become available in the future.

Keywords: Ozone, chemical transport model, statistical benchmark, uncertainty analysis, China

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1 Introduction

Tropospheric ozone (O_3) is a secondary air pollutant generated by complicated photochemical reactions involving nitrogen oxides (NO_x) and volatile organic compounds (VOC) (Seinfeld and Pandis, 2016). Ozone has negative impacts on human health (GBD, 2021), vegetation and ecosystem productions (Ainsworth et al., 2012). Due to rapid economic development and fast industrialization and urbanization over the past several decades, China has experienced heavy haze pollution in winter and severe O_3 pollution in summer, the latter extending into the late-winter haze season (Li et al., 2021). Despite efforts to reduce fine particulate matter ($PM_{2.5}$) and heavy haze days (Wang et al., 2022; Bai et al., 2019; Chu et al., 2020), ground-level O_3 concentrations have continued to increase in recent years (Dang and Liao, 2019; Li et al., 2019; Liu et al., 2019a; Lu et al., 2020; Wang et al., 2017; Yao et al., 2023; Chen et al., 2023; Xu et al., 2023). The challenge in controlling O_3 pollution lies in the significant influences of meteorological conditions on O_3 formation and its nonlinear relationship with precursors (Wang et al., 2022b). In addition, O_3 pollution exhibits strong regional characteristics, necessitating regional-scale control efforts (Yang et al., 2021a).

Application of chemical transport models (CTMs) has become increasingly popular in addressing O_3-related issues in China (Yang and Zhao, 2023), providing insights into the role of local emissions and regional transport (Shen et al., 2022), sectoral contributions (Liu et al., 2020a), policy effectiveness (Liu et al., 2023b), and predictions of future O_3 levels (Yang and Zhao, 2023). Ensuring the representativeness of CTM simulations is crucial, and can benefit from establishing performance standards or benchmarks to help put CTM results in context relative to the existing body of work. While other regions (e.g., the U.S. and Europe) have proposed evaluation criteria for simulated O_3 (Emery et al., 2017), they may not be suitable for China. The increasing prevalence of CTM applications in China necessitates specific CTM benchmarks tailored to this region.

This study aims to develop customized CTM benchmarks for O_3 simulations in China, building upon our prior work that proposed evaluation indicators and benchmarks for simulating other criteria air pollutants (Huang et al., 2021; Zhai et al., 2024). A thorough literature review was conducted on O_3 simulations using CTMs from 2006 to 2021. Detailed information regarding O_3 performance was extracted and analyzed to recommended model performance evaluation (MPE) metrics and to propose benchmarks tailored to China. Furthermore, uncertainties in O_3 predictions due to various model inputs were quantified using the decoupled direct method of sensitivity analysis (DDM, Cohan and Napelenok, 2011) in a commonly used CTM. The structure of this study is as follows: Section 2 outlines the data source and methodology utilized. Section 3 describes the current status of O_3 simulation studies in China and proposes recommended evaluation metrics and associated benchmarks. Section 4 delves into discussions on O_3 uncertainties arising from different model inputs and conclusions are given in Section 5.

2 Methodology

2.1 Data collection

The methodology for data compilation was consistent with our prior studies for other criteria pollutants (Huang et al., 2021; Zhai et al., 2024) and is briefly described here. We considered published O_3 simulations using five CTMs: the Community Multiscale Air Quality (CMAQ, https://www.epa.gov/cmaq, accessed on 2024-07-12) model, the Comprehensive Air quality Model with extensions (CAMx, https://camx.com, accessed on 2024-07-

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12), the Goddard Earth Observing System coupled with chemistry (GEOS-Chem, https://geoschem.github.io, accessed on 2024-07-12), the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem, https://www2.acom.ucar.edu/wrf-chem, accessed on 2024-07-12), and the Nested Air Quality Prediction Modeling System (NAQPMS) (Wang et al., 2014; Ge et al., 2014). We gathered relevant publications using a combination of three keywords in Web of Science: "O_3", the models' names (one of the five models), and "China", with a time range between 2006 and 2021. This process identified a total of 667 records (250 studies for CMAQ, 186 for WRF-Chem, 163 for GEOS-Chem, 36 for CAMx, and 32 for NAQPMS), with subsequent refinement steps to exclude duplicates, non-English publications, conference papers, and journals unrelated to air quality. Through manual selection, which involved identifying studies that provide extractable results (i.e., studies offering explicit results from model performance evaluations), a final set of 216 studies was chosen for detailed analysis (see Table S1 for a complete list of publications).

Detailed information regarding model configurations (e.g., modeling period, spatial resolution, gas-phase chemistry, initial/boundary conditions) and results of 23 MPE metrics (Table S2) were extracted and compiled from those 216 studies. For consistency, we converted O_3 concentrations reported in parts per billion by volume (ppbv) to $\mu g/m^3$ using a factor of 2.14 (equivalent to 273.15 K at 101.325 kPa) for consistency. Ten regions in China (Table S3), including the Beijing–Tianjin–Hebei (BTH) region, Yangtze River Delta (YRD) region, Pearl River Delta (PRD) region, Sichuan Basin (SCB), North China Plain (NCP), and five other regions (Figure 1), were identified for further analysis.

2.2 Recommended benchmarks for O_3

Among the 23 collected MPE metrics, we derived recommended benchmarks for the six most frequently used metrics (see Table S4 for definitions): mean bias (MB), normalized mean bias (NMB), root mean square error (RMSE), normalized mean error (NME), correlation coefficient (R), and index of agreement (IOA). The derivation of benchmarks follows previous studies by Simon et al. (2012) and Emery et al. (2017). Briefly, each metric's rank-ordered (from best to worst, for instance, from 1 to 0 for R) distribution was generated to identify the values at the 33rd and 67th percentiles. As highlighted in Emery et al. (2017), these percentiles serve to categorize the entire distribution into three performance categories: studies falling within the 33rd percentile (the "goal") attain the best performance that current models can be expected to acheive, those between the 33rd and 67th percentiles (the "criteria") attain typical performance achieved by the majority of modeling studies, while those beyond the 67th percentile indicate relatively poor performance for the particular metric under consideration. We present the benchmarks for hourly O_3, maximum daily 8-hr average O_3 (8-hr max O_3), and daily maximum 1-hr O_3 (1-hr max O_3), depending on data availability.

2.3 Uncertain analysis of O_3 simulation

In addition to developing the MPE benchmarks for simulated ozone, we further quantified uncertainties in predicted ozone concentrations using one of the five models (i.e., CMAQ). The CMAQ version 5.3.2 (https://www.epa.gov/cmaq, accessed on April 17, 2024) was employed to simulate O_3 during June 2021 in China. Base model configurations are the same as our previous study (Sun et al., 2024) and are briefly described here. The modeling domain covers the entirety of China and adjacent Asian regions (Figure 1) with a spatial resolution of 36 km × 36 km grid and 23 vertical layers. Meteorological fields are simulated using the Weather

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Research and Forecasting model (WRF version 4.0). CB6 and AERO7 were chosen as the gas-phase and aerosol mechanisms, respectively. Emissions data include the 2019 Multi-resolution Emission Inventory for China (MEIC-2019) (http://www.meicmodel.org, accessed on June 23, 2022) and the 2010 Emissions Database for Global Atmospheric Research (EDGAR, http://www.meicmodel.org, accessed on June 23, 2022). Natural emissions were generated based on the Model of Emissions of Gases and Aerosols from Nature (MEGAN version 3.1, https://bai.ess.uci.edu/megan, accessed on June 23, 2022). The CMAQ default O_3 profile (with a uniform O_3 concentration of 29 ppb) was used as the initial and boundary conditions (BCs). A 10-day spin-up run was conducted to mitigate the influence of initial conditions.

We followed Dunker et al. (2020) to quantify the uncertainties of predicted O_3 concentrations due to six model inputs: anthropogenic NO*x* (ANO*x*) and VOC (AVOC) emissions for China, biogenic VOC (BVOC) and soil NO*x* (SNO*x*) within China; dry deposition velocities for O_3; and BCs for O_3. The uncertainties associated with each of the inputs (Table S5) are based on previous studies addressing emission uncertainties (Cheng et al., 2019), deposition velocities, and BCs (Beddows et al., 2017; Derwent et al., 2018). Like Dunker et al. (2020), these uncertainties were considered independent and lognormally distributed. The CMAQ decoupled direct method (DDM) was used to generate first-order sensitivities of O_3 to each of the inputs (excluding dry deposition). For dry deposition, we conducted two parallel simulations in which the O_3 dry deposition velocities were manually changed by ±10%, and the changes in simulated O_3 concentrations were treated as the O_3 sensitivities to dry deposition velocity:

$$S_{DEP}^{(1)} = \frac{C_{1.1dep\_O_3} - C_{0.9dep\_O_3}}{2} * 10 \qquad \text{Eq. (1)}$$

where $S^{(1)}_{DEP}$ is the O_3 sensitivity to dry deposition velocities, and $C_{1.1dep\_O3}$ and $C_{0.9dep\_O3}$ represent the simulated O_3 concentrations as dry deposition velocities are increased and decreased by 10%, respectively. The sensitivities obtained were then combined with their respective uncertainties, enabling us to quantify the contributions to the variance in O_3 concentrations. For example, the O_3 uncertainties due to dry deposition are calculated as:

$$\text{un(DEP)} = var(DEP) = \left[\frac{\ln(f_{DEP})}{2} * S_{DEP}^{(1)}\right]^2 \qquad \text{Eq. (2)}$$

where un(DEP) represents the uncertainty of O_3 due to dry deposition at 1σ, and f_{DEP} (=2 from Table S5) is the uncertainty factor for dry deposition and follows an assumpation of a lognormal distribution.

The contribution of dry deposition to the total uncertainty in O_3 is calculated as follows:

$$\%\, DEP = \frac{var(DEP)}{var(ANOx) + var(AVOCs) + var(BNOx) + var(BVOCs) + var(DEP) + var(BCs)} \qquad \text{Eq. (3)}$$

3. Results and discussions

3.1 General overview of O_3 simulation studies in China

In the last decade, there has been a significant increase in research focusing on O_3 in China, as illustrated in Figure 2. The issuance of the Three-Year Action Plan to Win the Blue Sky Defense Battle in 2017 (http://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm, accessed on April 15, 2024) led to a further surge in studies related to O_3, with a noticeable decline in 2020 possibly attributed to the impact of the COVID-19 pandemic. In 2021, there were 48 studies dedicated to addressing O_3-related issues using CTMs, marking a six-fold increase compared to 2011. Similar to $PM_{2.5}$, BTH (74 studies), YRD (59 studies), and PRD (58 studies) emerged as the top three most studied regions. Among the various CTMs employed, CMAQ stood out as the most commonly utilized model (90 studies), followed by WRF-Chem (84 studies). The application of CAMx (14 studies) and NAQPMS (8 studies) was relatively less frequent. In terms of MPE metrics, R had the highest frequency of occurrence at 19%, followed by NMB (18%), MB (16%), RMSE (13%), and NME (11%). Nearly half of the studies incorporated 2 or 3 metrics for evaluating O_3, while less than 7% assessed at least five different metrics. The three most common types of O_3 concentrations evaluated were hourly O_3 concentration, the maximum daily 8-hour average O_3 (8-hr max O_3), and the daily maximum 1-hour O_3 (1-hr max O_3). Among all the articles examined, 77% focused on evaluating hourly O_3, 16% on 8-hr max O_3, and 7% on 1-hr max O_3.

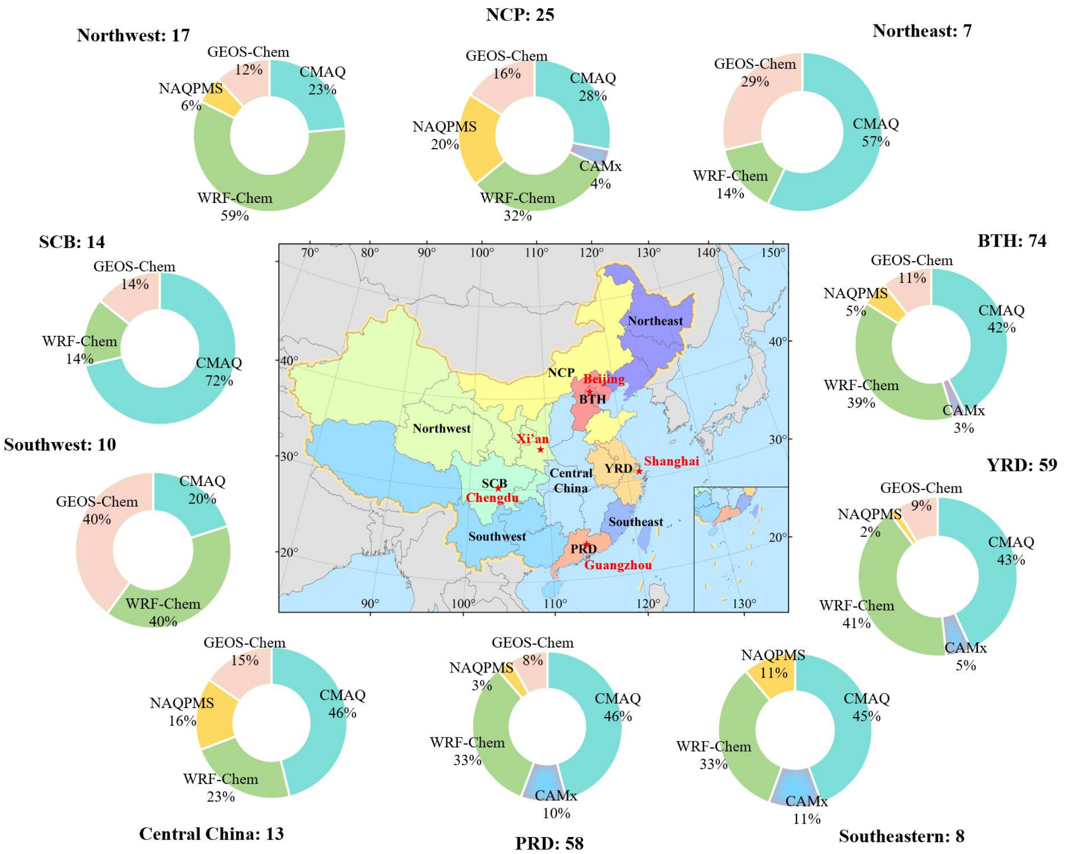

Figure 1 CMAQ modeling domain with definitions of regions used in this study. The surrounding pie charts display the total number of studies for each region (excluding studies for the entire China) and the percentage of different CTMs used. Red stars represent the five cities selected in uncertainty analysis.

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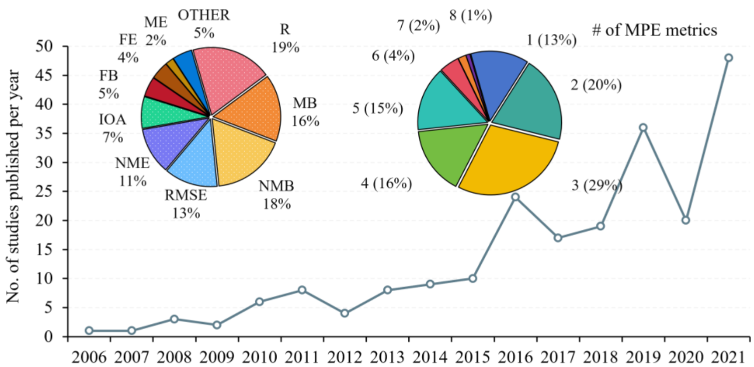

Figure 2 Number of O_3 studies published during 2006–2021. Pie charts show the frequency of different MPE metrics (left) and the number of metrics used in one study (right).

3.2 Quantile distributions of O_3 MPE results

Figure 3 shows the quantile distributions of various evaluation metrics collected in this study. The results are presented for different types of O_3 concentrations: hourly O_3, 1-hr max O_3, and 8-hr max O_3, whenever data is available. Previous studies have shown that using maximum O_3 values (i.e. 1-hr max and 8-hr max) instead of hourly O_3 can lead to differing results within the same study (e.g., Ni et al., 2020; Li et al., 2016). Peak O_3 concentrations typically occur between 12:00 and 18:00. For example in Ni et al. (2018), 8-hr max O_3 showed an overestimation tendency compared to average hourly O_3, but in another study (Yang et al., 2021b), there was an opposite trend. Underestimation of peak O_3 concentrations might be offset by overestimation during non-peak hours and vice versa. Therefore, achieving satisfactory performance in daily averaged O_3 levels does not necessarily indicate the model's ability to accurately capture high O_3 concentrations.

Hourly O_3 exhibited equivalent overestimation and underestimation in terms of MB and NMB, with MB ranging from as low as -40 μg/m^3 to nearly 50 μg/m^3 and NMB ranging from less than -50% to more than 70%. However, fractional bias (FB) indicated more underestimated than overestimated hourly O_3 concentrations. For all three bias metrics, 8-hr max O_3 exhibited more overestimation than underestimation, suggesting a tendency for models to overestimate off-peak hours. For 1-hr max O_3, both NMB and FB displayed equivalent overestimation and underestimation, with NM showing a wider range than FB, likely due to fewer data points. For error metrics, 8-hr max and 1-hr max O_3 generally performed better than hourly O_3. For instance, the median values of NME were 34.8%, 26.6%, and 29% for hourly O_3, 8-hr max, and 1-hr max O_3, respectively. R and IOA indicate how well the model captures observed variations, either temporally or spatially. The use of IOA was significantly less than R and no studies reported IOA values for 1-hr max O_3. For the other two O_3 types, IOA values (median value of 0.8 for O_3 and 0.77 for 8-hr max O_3) were generally higher than R (median value of 0.69 for O_3 and 0.66 for 8-hr max O_3). Six studies reported both R and IOA values, of which four (Liu and Wang, 2020; Wang et al., 2019; Liu et al., 2019b; Gao et al., 2017) reported higher IOA values than R.

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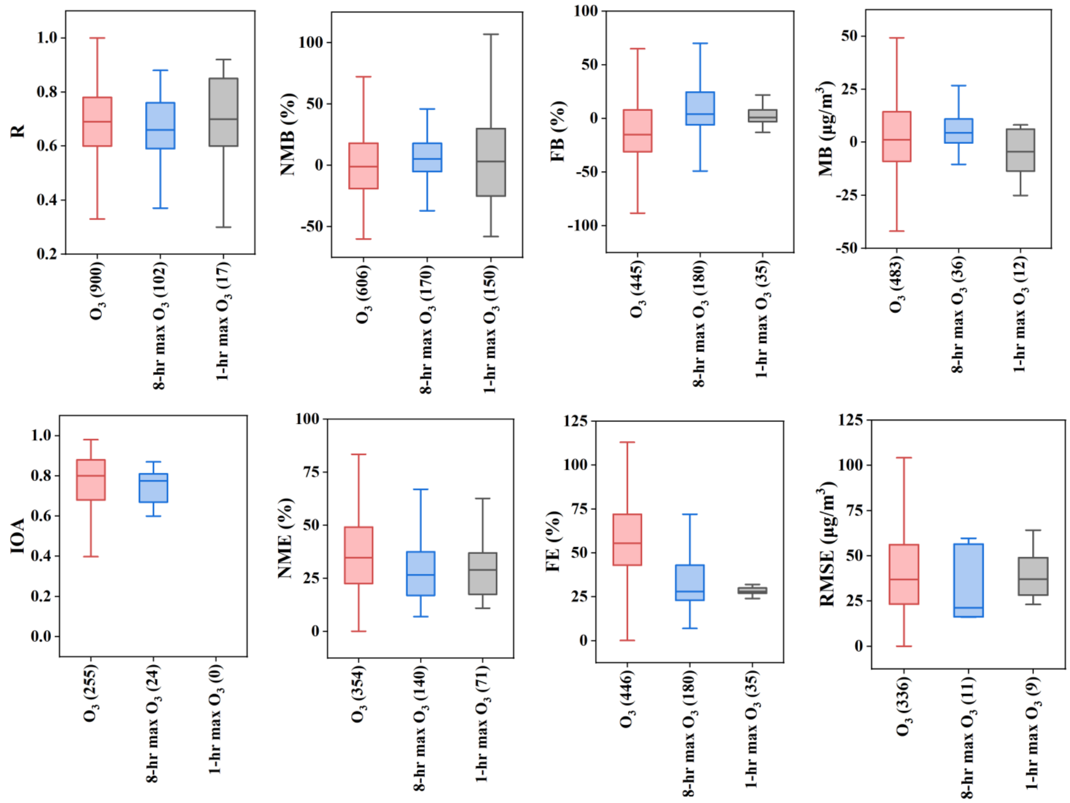

Figure 3 Quantile distribution of common O_3 performance indicators

Regional and seasonal differences

Like our previous studies (Huang et al. 2021; Zhai et al. 2024), we discuss the influences of various key factors on model performance in simulating O_3 concentrations. We first considered whether there were discernible regional or seasonal differences. Figure 4 presents the distribution of R and NMB values grouped by three key regions in China: BTH, YRD, and PRD. These regions are the most densely populated and economically developed urban clusters in China. In terms of hourly O_3, the R values across the three regions display similarity, with median values around 0.7. For 8-hr max O_3, however, PRD stands out with notably lower R values compared to BTH and YRD. Regarding NMB values, BTH tends to have more underestimation, while the YRD and PRD lean towards overestimation. Over the past decade, BTH has consistently recorded the highest O_3 levels and number of O_3 pollution days among the three regions (Wang et al., 2024). The variations in NMB values among regions suggest a trend of current models underestimating O_3 levels in areas with more severe O_3 pollution.

In terms of the seasonal variations (Figure 5), the NMB values of hourly O_3 concentrations exhibit similar patterns across different seasons, showing equivalent overestimation and underestimations. However, when assessed over the entire year, hourly O_3 concentrations tend to be largely underestimated. The seasonal patterns of NMB distributions are similar for 8-hr and 1-hr max O_3, with summer O_3 concentrations being more frequently underestimated compared to other seasons. For instance, in the case of 1-hr max O_3, peak O_3 concentrations are

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predominantly underestimated (with a median NMB of -23%) while they are overestimated in winter (with a median NMB of 31.5%).

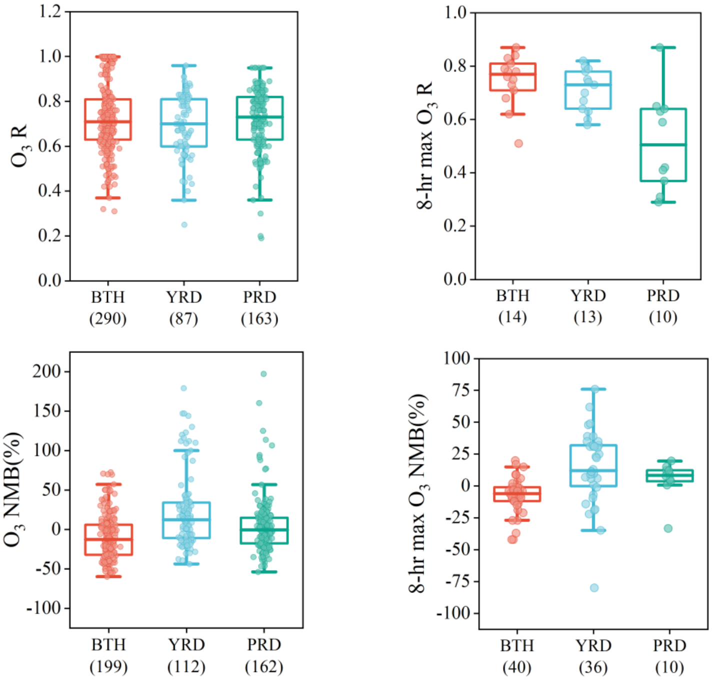

Figure 4 Quantile distribution of R and NMB of O_3 in BTH, YRD, and PRD

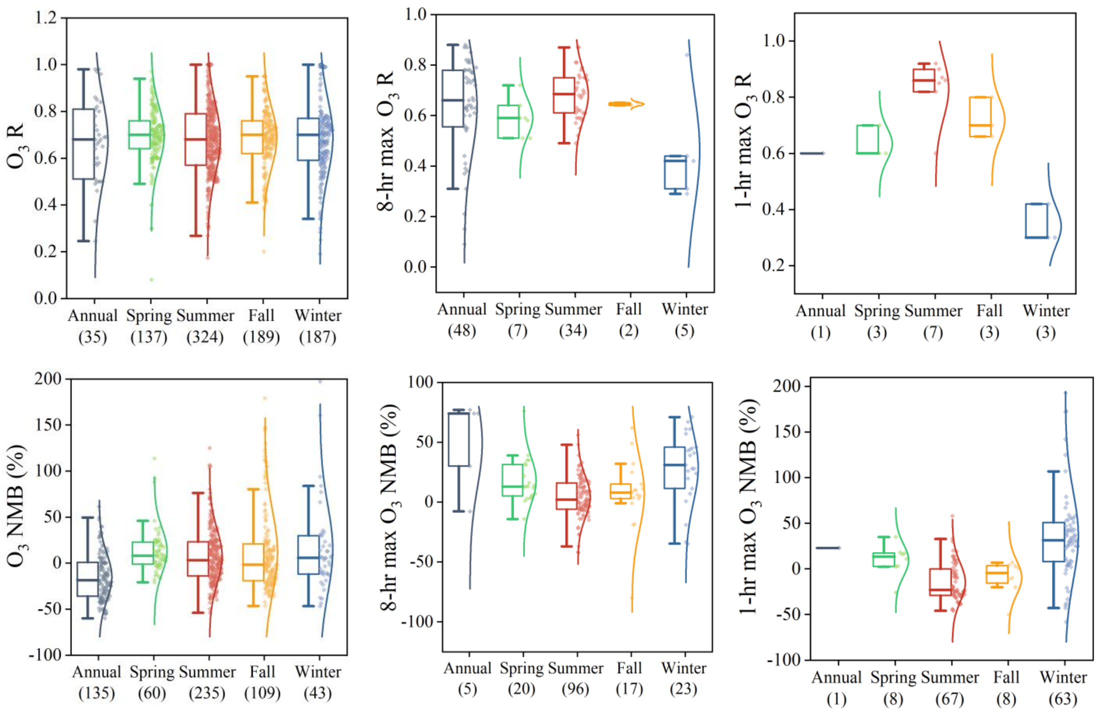

Figure 5 Quantile distribution of O_3 NMB values in different seasons

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Impact of grid spacing

The selection of grid spacing for a CTM application depends on several factors, such as the objective of the study, the geographical scope of the study area, the availability of input data, etc. Generally, a coarse grid spacing (> 50 km) is utilized for global simulations (i.e. GEOS-Chem), while a finer grid spacing (< 4km) with nested grids is preferred for regional or city-scale modelling. Coarser grid spacing may result in multiple monitoring stations falling within a single grid cell, potentially smoothing out extreme values observed at specific locations. Among the 216 studies reviewed, 29 different grid resolutions (based on the resolution of the innermost domain) were identified, ranging from 1 km to 200 km. The resolutions were classified into five groups in this study: < 5 km, 5-10 km, 10-25 km, 25-50 km, and 50-100 km (resolutions over 100 km were excluded from the analysis due to limited data points). Figure 6 shows the distribution of eight statistical indicators by different resolutions. Overall, no clear trend was evident to indicate better model performances as grid spacing decreases. For example, the median R value is 0.73 for < 5 km group, surpassing the 5-10 km and 25-50 km groups but falling below the 10-25 km and 50-100 km groups. Studies conducted with a grid spacing of 10-25 km exhibit the best model performance in terms of NME and FE distributions compared to other groups. While most studies assess models within a single domain (usually the innermost domain with the finest resolution), a few studies have conducted multi-domain analyses, where finer spatial resolutions generally have superior results compared to coarse resolutions. Liu et al. (2020b) used WRF-CMAQ to analyze O_3 prediction and health exposure at different spatial resolutions (1, 4, 12, and 36 km). The results showed more than 20% difference in premature mortality due to different model resolutions being used. Nevertheless, reducing grid spacing does not necessarily lead to improved model performance if the input data resolution (i.e., spatial resolution of the emissions) is not correspondingly high or well-matched.

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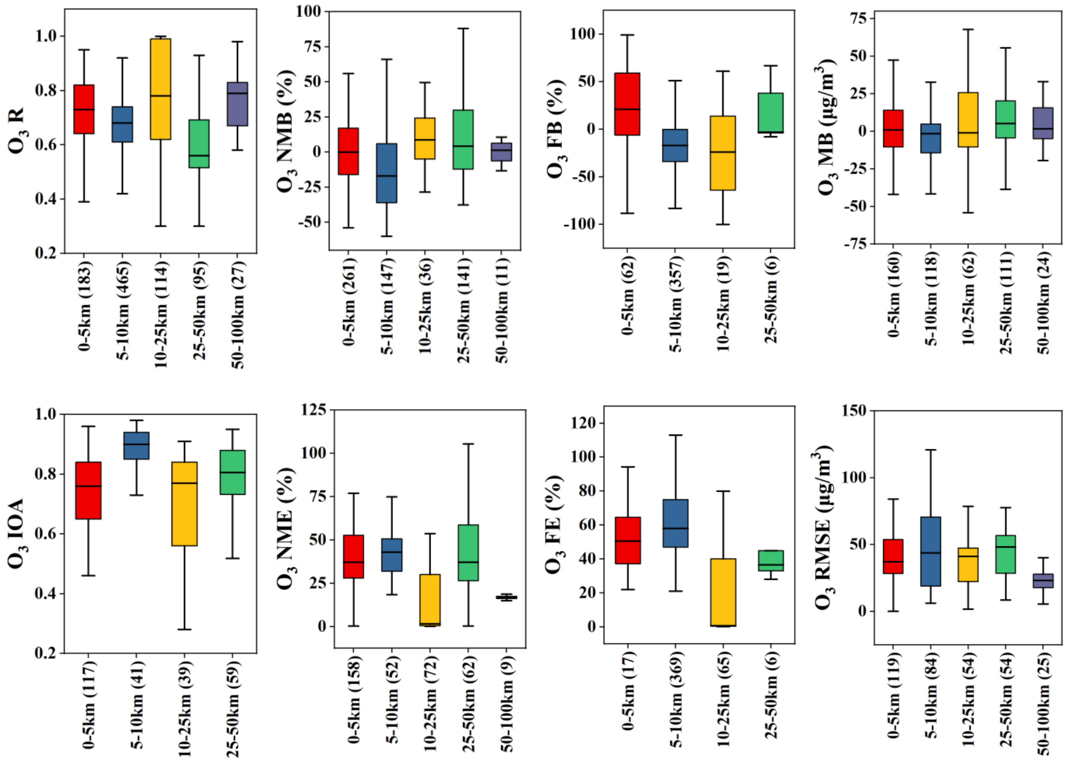

Figure 6 Quantile distribution of O_3 with respect to commonly used assessment indicators at different spatial resolutions

Choice of gas-phase chemical mechanism

Gas-phase chemical mechanisms play a crucial role in the accurate prediction of atmospheric composition using CTMs. Some of the commonly used mechanis
ms include the Carbon Bond mechanism (CB) (Yarwood et al. 1997; Luecken et al., 2019; Appel et al., 2021; Yarwood and Tuite, 2024), the Statewide Air Pollution Researcher Center (SAPRC) mechanism (Carter, 1996; Chang et al., 1999; Carter, 2000; Carter, 2010), and the Regional Atmospheric ChemistryMechanism (RACM) (Stockwell et al., 1997; Goliff et al., 2013). These mechanisms have undergone rigorous evaluations against experimental data, showcasing reliable predictive capabilities for O_3 in diverse atmospheric environments. The CB mechanism is a condensed mechanism in which the carbon bond is treated as a reaction unit, and the carbon bonds with the same bonding state are treated as a group (Cao et al., 2021). The latest version, CB7, contains 91 gaseous species and 230 reactions (https://www.tceq.texas.gov/downloads/air-quality/research/reports/photochemical, accessed on 2024-06-18). In contrast, the SAPRC mechanism categorizes species based on their reactivity with OH (Carter et al., 2010). The most recent SAPRC22 mechanism includes 162 species and 738 reactions. RACM was developed based on Regional Acid Deposition Model (RADM), which is an inductive mechanism for treating hydrocarbons with fixed parameterization method and is carried out according to the reaction rate and activity of different pollutants with ·OH. Compared to the other two mechanisms, RACM and RACM2 contain detailed chemical processes of radicals, biogenic VOC and less-reactive VOC able to survive during long distance transport. 119 reactive species and 363 reactions were

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included in RACM2 describing the oxidation reactions of 21 types of primary VOC in the system (Liu et al., 2023a).

Among the 216 studies compiled, nearly half of them used CB mechanism for simulations, approximately a quarter employed RACM/RADM, and only 15 studies utilized SAPRC. Figure 7 compares the distribution of R and NMB grouped by different gas-phase mechanism. In terms of R values, CB tends to perform slightly better than RACM/RADM, with SARPC showing the highest R median value (0.93) for hourly O_3 but the lowest for 8-hr max O_3 among the three mechanisms. Regarding NMB, SAPRC tends to overestimate peak O_3 values compared to the other mechanisms, particularly for 1-hr max O_3, a trend observed in previous studies (Qiao et al., 2019).

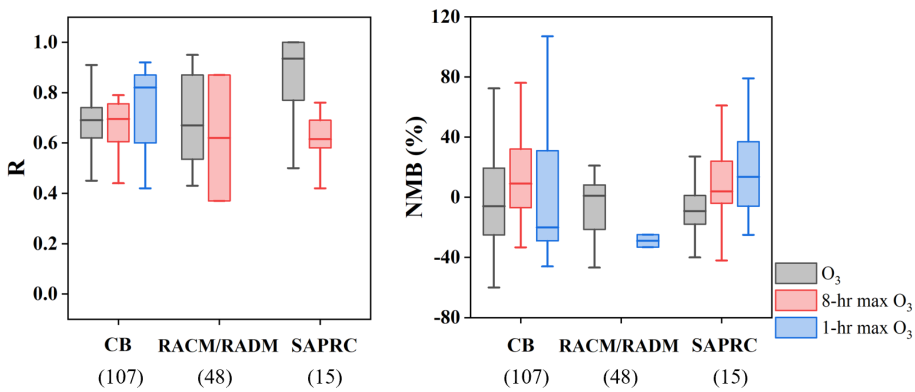

Figure 7 Quantile distributions of R and NMB by gas-phase chemical mechanism

3.3 Recommended benchmarks for O_3 MPE

Figure 8 illustrates the ranked distributions of various statistical indicators, including R, IOA, NMB, NME, FB, and FE for hourly O_3, 1-hr max O_3, and 8-hr max O_3. The absolute values of NMB and FB are presented to indicate deviations from zero. In terms of R and IOA, the ranked distributions for hourly O_3 and 8-hr max O_3 are quite similar, with R values ranging from around 0.72 at the 33rd percentile to 0.60 at the 67th percentile. The corresponding IOA values are slightly higher, ranging from ~0.83 at the 33rd percentile to ~0.73 at the 67th percentile. For 1-hr max O_3, the limited number of data points (less than 20) resulted in an R value of 0.80 at the 33rd percentile and 0.60 at the 67th percentile, while the IOA distribution was not available due to missing data. For NMB and NME, the results for 8-hr max O_3 show the lowest values, indicating that models perform better in capturing the 8-hr max O_3 concentrations. The 33rd percentile of absolute NMB for 8-hr max O_3 is less than 10%, and the 67th percentile is below 20%. In terms of FB and FE, the ranked distributions for 1-hr max O_3 are flatter compared to the other two O_3 types, likely due to the smaller number of available data points. For both metrics, the 8-hr max O_3 exhibits lower values than O_3. At the 33rd percentile, the absolute FB (FE) is less than 10% (25%) for 8-hr max O_3 and less than 20% (50%) for O_3. At the 67th percentile, the absolute FB (FE) is 25% (38%) for 8-hr max O_3 and 34% (65%) for O_3. In addition, we provide a more detailed ranked distribution in Table S6.

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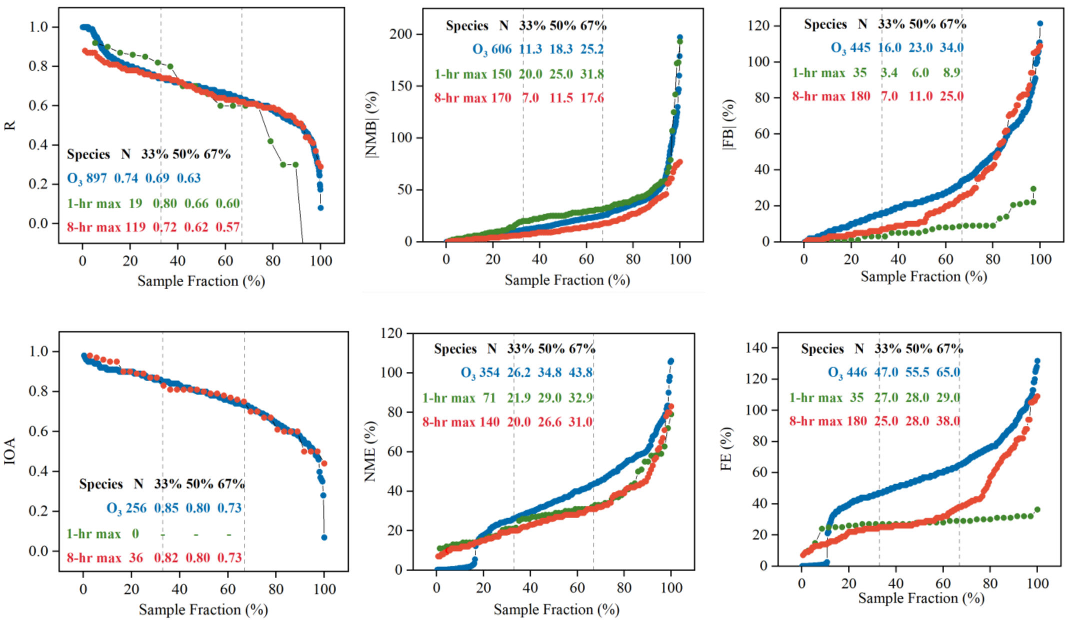

Figure 8 Rank-ordered distributions of R, IOA, NMB, NME, FB, and FE for O_3, 1-hr max O_3 and 8-hr max O_3 speciated components. The number of data points and the 33rd, 50th, and 67th percentile values are also listed.

Following Emery et al. (2017) and Huang et al. (2021), we propose recommended statistical indicators and corresponding benchmarks for evaluating O_3, as detailed in Table 1. The goal values, corresponding to the threshold at the 33rd percentile, represent the optimal model performance anticipated from current models. The criteria values, reflecting the threshold at the 67th percentile, represent the performance levels achieved by the majority of studies. Due to limited data availability, the derivation of benchmarks for certain metrics concerning 1-hr max O_3 remains uncertain. In such cases, benchmarks for IOA and R for hourly O_3 were directly adopted due to minimal variations among different O_3 types. Similarly, benchmarks proposed for 8-hr max O_3 were applied to 1-hr max O_3 for FB and FE, given their closer distributions. Our findings indicate that benchmarks tend to be more stringent for 8-hr max O_3 compared to the other two types, with the exception of IOA where they remain the same. Based on our results, a value of R greater than 0.70 and 0.55 would meet the goal and criteria benchmark for 8-hr max O_3. Correspondingly, the goal and criteria values for NMB are 10% and 20%.

In contrast to Emery et al. (2017), we provide separate benchmarks for O_3, 8-hr max O_3, and 1-hr max O_3. Emery et al. (2017) found rather similar results between hourly and 8-hr max O_3 in the U.S and so recommended a single set of benchmarks for ozone. Out of the 216 studies analyzed, 15 studies evaluated at least two O_3 types. The use of cutoff for evaluating O_3 is extremely limited in China (only 5 studies applied cutoffs), thereby precluding any specific recommendation on cutoff values. In addition to the benchmarks for NMB, NME, and R provided by Emery et al. (2017), we have introduced benchmarks for IOA, FB, and FE, backed by a sufficient number of data points. The few values marked with an asterisk in Table 1 indicate that our benchmarks are more stringent than the corresponding values in Emery et al. (2017), implying that achieving our recommended 33rd (or 67th) percentiles may pose greater challenges.

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Overall, however, our proposed benchmarks are more lenient than those of Emery et al. (2017), particularly in the context of hourly O_3. For NME, our suggested goal and criteria for O_3 stand at 30% and 45%, respectively, nearly double the figures reported by Emery et al. (2017), which recommend 15% for the goal and 25% for the criteria. The criteria value for R is an exception where our proposed value (0.55 for 8-hr max O_3 and 0.60 for O_3) is higher than 0.50 in Emery et al. (2017).

Table 1 Recommended benchmarks for evaluating simulated O_3 by CTM applications in China

Metrics	Benchmark level	O_3	8-hr max O_3	1-hr max O_3	Emery et al. (2017) 1-hr max O_3 and 8-hr max O_3
R	Goal	> 0.70	> 0.70	> 0.80*	> 0.75
	Criteria	> 0.60*	> 0.55*	> 0.60*	> 0.50
NMB	Goal	< ±15%	< ±10%	NA	< ±5%
	Criteria	< ±30%	< ±20%	NA	< ±15%
NME	Goal	< 30%	< 20%	< ±20%	< ±15%
	Criteria	< 45%	< 35%	< ±35%	< ±25%
IOA	Goal	> 0.80	> 0.80	< 25%	NA
	Criteria	> 0.70	> 0.70	< 35%	NA
FB	Goal	< ±20%	< ±10%	< ±5%	NA
	Criteria	< ±35%	< ±30%	< ±10%	NA
FE	Goal	< 50%	< 25%	< 25%	NA
	Criteria	< 65%	< 40%	< 30%	NA

Note. (1) See descriptions in the main text for bold values. (2) Values with an asterisk indicate that our benchmarks are stricter than the corresponding values in Emery et al. (2017).

4. Uncertainty analysis of O_3 simulation using CMAQ

In order to further investigate the uncertainties in simulated O_3 concentrations simulated by CTMs, a base model simulation was conducted using CMAQ (the most frequently used CTM in China) for June 2021, a typical month with elevated O_3 in northern and eastern China. The uncertainties due to six model inputs were quantified for this case: VOC and NO*x* emissions in China, differentiation between anthropogenic and biogenic sources, O_3 dry deposition velocities, and boundary conditions (BCs). The evaluation of the base model results indicates generally acceptable simulated MDA8 O_3 concentrations when compared to the observations. The results showed an overall MB of 6.1 $\mu g/m^3$ and NMB of 5.2% (Figure 9). O_3 underestimation is observed over the BTH region, while overestimation occurs over the Sichuan Basin. The values of NMB, NME and R meet the goal benchmark we proposed above.

As displayed in Figure 10, the first-order sensitivity of MDA8 O_3 to the six model inputs exhibits substantial variations in spatial distributions and magnitudes. Higher sensitivity occurs in larger urban areas and is relatively low in rural areas. The sensitivity to VOC emissions is always positive (i.e., higher VOC leads to higher O_3), whereas the sensitivity to NO*x* emissions could be both positive and negative. High O_3 sensitivity to AVOC emissions is observed for BTH, northern YRD, PRD, and major metropolitan areas (e.g., Chengdu in Sichuan

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province, Xi'an in Shaanxi province), due to NOx-rich and VOC-limited urban conditions. Conversely, anthropogenic NO*x* emissions resulted in negative O_3 sensitivity in the aforementioned regions and positive sensitivity in others where rural conditions are more VOC-rich and NO*x*-limited. The sensitivity to biogenic precursor emissions (BVOC and SNO*x*) was much lower compared to their anthropogenic counterparts. The sensitivity to O_3 BCs predominantly extends towards the northwest (up to 50 μg/m^3), where O_3 precursor emissions are low. The sensitivity to O_3 dry deposition velocity exhibits a uniformly negative distribution (higher deposition rates lead to lower ozone), with higher values in more vegetated areas and an average of -13.7 μg/m^3.

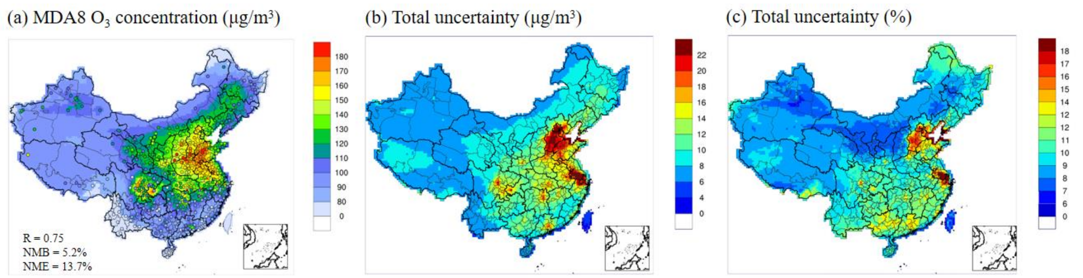

Figure 9 Spatial distributions of (a) MDA8 O_3 concentrations (ug/m^3), (b) total uncertainties in μg/m^3, and (c) total uncertainty in percentage (%). Results are averaged for June 2021.

When the individual first-order sensitivity coefficient multiplies by the corresponding 1σ uncertainty (Table S5), the contributions to the uncertainty in O_3 predictions can be obtained (Figure 10). Summing up all these uncertainties yields the total uncertainty (Figure 9b). Large ozone uncertainties (> 20 μg/m^3) were observed over BTH, central YRD region, and major metropolitan areas (e.g. PRD, Chengdu in Sichuan province). Regions with high uncertainties in O_3 predictions generally align with regions with poorer model performance. In BTH, YRD, and PRD, the total ozone uncertainty due to the six model inputs ranges 11.7~31.8, 7.0~34.6 and 5.0~19.0μg/m^3, respectively, corresponding to a relative percentage of O_3 concentration by 9.2~18.1%, 7.9~25.8%, and 7.6~14.6%. It should be noted that our uncertainty estimates represent conservative estimates because the effects of uncertainties in the meteorological inputs and the uncertainties associated with the O_3 chemistry are not included, the latter of which has been shown to have a comparable contribution to the total contributions from emissions, dry deposition, and O_3 BC in the Dallas-Fort Worth region in the U.S. (Dunker et al. 2020).

Among the six model inputs, AVOC emissions make the largest contributions (exceeding 15 μg/m^3) to the total uncertainty in regions displaying high O_3 sensitivity, such as BTH, northern YRD, PRD, and several metropolitan areas. The large uncertainties, stemming from both the high first-order sensitivities (Figure S1) and a relatively high uncertainty factor (1.68), suggest that in these regions, uncertainties associated with AVOC emission estimates would in more significant biases in simulated O_3 concentrations compared to other areas. O_3 uncertainties due to BVOC emissions, ranging 0.1~10.4 μg/m^3, are mainly located in southern China, where BVOC emissions are high. A similar spatial pattern is observed for uncertainties in ANO*x* emissions, although its contribution is larger (0.5~11.9 μg/m^3). While the first-order O_3 sensitivity to SNO*x* emissions is minimal (Figure S1), the contribution to O_3 uncertainty from SNO*x* emissions is noteworthy (0.5~9.7 μg/m^3), given a large uncertainty factor of 2 (Table S5). Uncertainty in O_3 BCs is relatively less important except in the northwest, where it represents the largest contributing factor. Dry deposition serves as an important O_3 sink. Uncertainty contribution from O_3 dry deposition velocities (0.3~10.4 μg/m^3) is comparable to that of ANO*x* emissions, with a more evenly distributed spatial impact.

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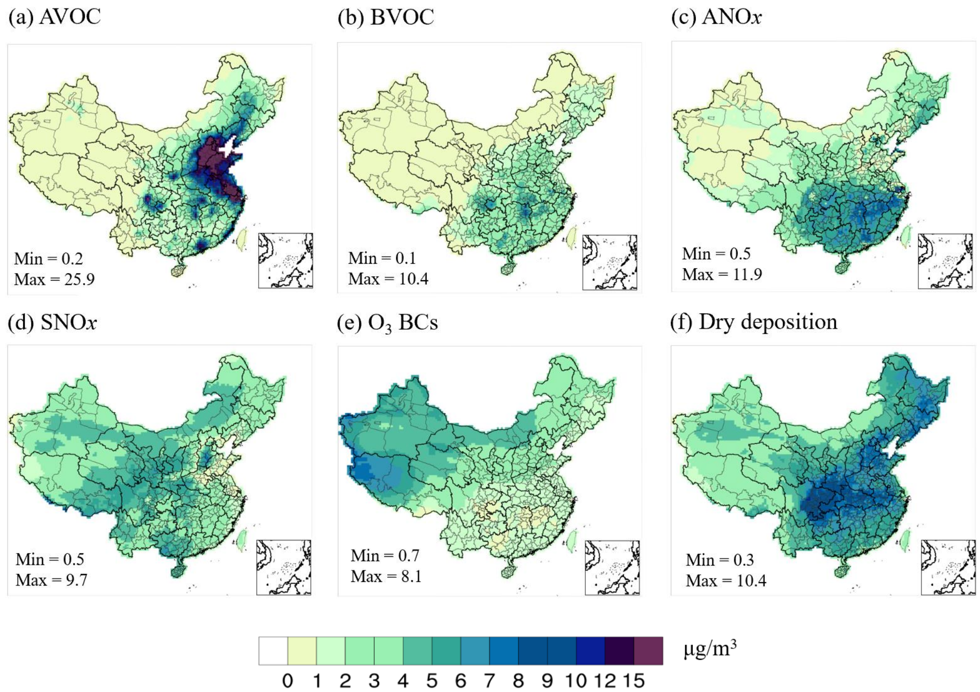

Figure 10 Contributions to uncertainty in MDA8 O_3 simulation. Contribution of (a) AVOC, (b) BVOC, (c) ANO*x*, (d) SNO*x*, (e) O_3 BCs, and (f) dry deposition in $\mu g/m^3$. Results are averages over all days in June 2021 and represent 1σ.

Figure 11 compares the observed MDA8 O_3 to the model results with their ± 1σ uncertainty range for five major cities: Beijing, Shanghai, Guangzhou, Chengdu, and Xi'an. In Shanghai, the majority of the observed O_3 fall within the ± 1σ uncertainty range. However, in Beijing, Chengdu, and to a lesser extent in Guangzhou, the model tends to over-predict lower O_3 observations. In Xi'an, the model fails to capture the exceptionally high O_3 concentrations (MDA8 O_3 > 250 $\mu g/m^3$) on June 6th and 7th. Expanding the uncertainty limits to a ± 2σ range may encompass some of the lower O_3 observations but the current uncertainty estimates do not fully account for all the discrepancies between model results and observations. This discrepancy could be attributed to the coarse grid resolution (36 km) used in this study, which may not adequately resolve the impact of local emission sources. Furthermore, as mentioned earlier, uncertainties related to O_3 chemistry and meteorological inputs were not accounted for and should be quantified in future work.

The relative contributions to the total uncertainty are also shown in Figure 11. Across all five cities, uncertainties in the AVOC emissions contribute the most (43%~65%) while the relative importance of other model inputs differs by location. For example, O_3 BCs represent the second largest uncertainty source in Beijing (accounting for 18%) but are negligible in Guangzhou and Chengdu. In Shanghai and Guangzhou, uncertainties in ANO*x* emissions (10%~17%) become the second largest contributor. Uncertainties associated with BVOC emissions are minimal in Beijing and Shanghai but noteworthy (7~8%) in Guangzhou and Chengdu. O_3 deposition uncertainty contributes to 8~30% of the total uncertainty, with a higher contribution for cities located in the west.

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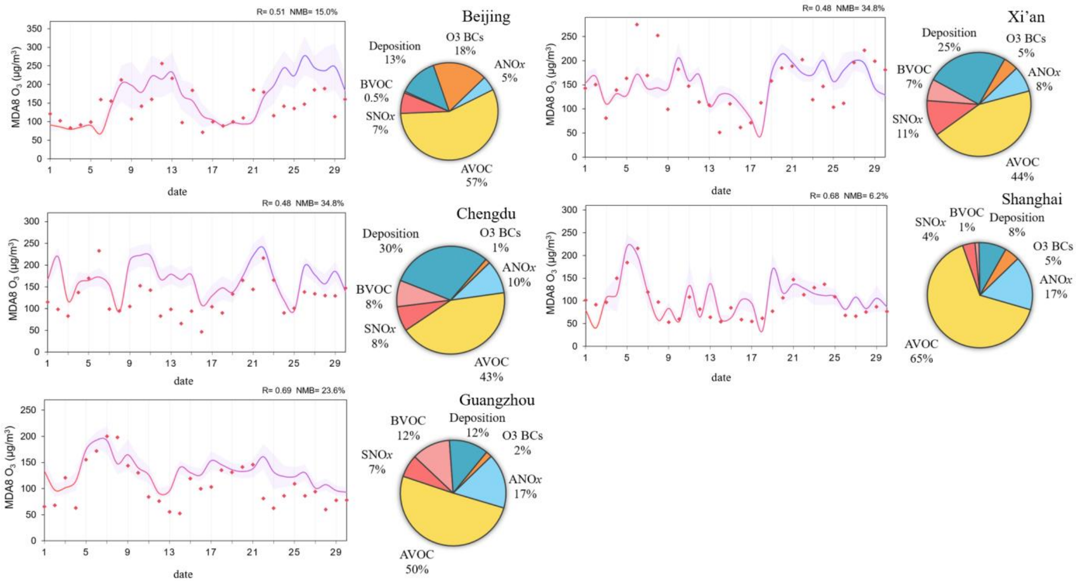

Figure 11 Compared with the average observation results of five urban monitoring points in June 2021, the uncertainty limit of MDA8 O_3 is ± 1 σ. The pie chart shows the contribution of each factor to the total uncertainty of the predicted average MDA8 O_3 in June 2021.

5. Conclusions

Chemical transport models are increasingly being employed to tackle the severe ozone pollution issues in China. This study involved the compilation and analysis of 216 peer-reviewed studies focused on the use of CTMs to simulate O_3 levels in China. Essential model configurations such as study region, simulation season, grid spacing, gas-phase mechanism, and quantitative model performance outcomes were systematically documented. The study presented quantile distributions of common statistical metrics found in the literature and discussed the influence of different model configurations on performance outcomes. Furthermore, we proposed benchmarks for six widely used MPE metrics (R, IOA, NMB, NME, FB, and FE) based on the concepts of "goals" and "standards" to offer guidance to modelers for a more consistent and contextual evaluation of models. Additionally, we utilized CMAQ-DDM to assess the uncertainties in predicted O_3 concentrations resulting from uncertainties in six model inputs. The findings revealed significant variations in spatial distributions and magnitudes of ozone sensitivity to different model inputs, with the most substantial contributions to total uncertainty originating from AVOC emissions in regions with high ozone sensitivity.

The proposed benchmarks for assessing simulated O_3 concentrations, in conjunction with previous studies on $PM_{2.5}$ (Huang et al. 2021) and other criteria air pollutants (Zhai et al. 2024), represent a comprehensive and systematic effort to establish a model performance framework for CTM applications in China. These outcomes not only offer valuable guidance to the growing modeling community in China but also support their endeavors in utilizing CTMs to address various research challenges and enhance air quality management.

Data availability. All data is available upon request from the corresponding author.

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Competing interests. At least one of the (co-)authors are members of the editorial board of journal ACP.

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