

A comprehensive review of tropospheric background ozone: Definitions, estimation methods, and meta-analysis of its spatiotemporal distribution in China

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Abstract. Background ozone (O₃) represents the baseline concentrations in the absence of local anthropogenic emissions and is critical for understanding and mitigating tropospheric O₃ pollution. Accurate estimation of background O₃ constrains the maximum achievable benefits of precursor emissions control and informs effective air quality management. This review synthesizes the definition and estimation methods for background O₃, including in situ measurement, statistical analysis, numerical modeling, and integrated methods. A meta-analysis of background O₃ in China from 1994 to 2020 reveals pronounced spatial variability, with concentrations ranging from 33 ppb in the Northeast China to 48 ppb in the Northwest China, and a national mean of 41 ppb, accounting for 79% of the tropospheric maximum daily 8-hour average O₃. Methodological discrepancies are evident for background O₃: in situ and statistical methods yield higher estimates, whereas integrated approaches produce lower yet more consistent values. Placed in a global context, background O₃ levels in China are medium-to-high and exhibit an increasing trend. This review highlights the need for integrated estimation methods to improve accuracy, underscores the international collaboration to address long-range pollutant transport, and calls for further research on the interactions between background O₃ and climate change. By advancing the understanding of background O₃ dynamics, it provides critical insights for atmospheric chemistry and air pollution control in China and beyond.

1 Introduction

Since the implementation of the “Air Pollution Prevention and Control Action Plan” in 2013 and the subsequent “Three-Year Action Plan for Winning the Blue Sky War”, China has achieved remarkable

improvement in air quality, particularly in reducing fine particulate matter (PM_{2.5}) concentrations. Nationwide PM_{2.5} levels declined by approximately 50% between 2013 and 2020 (Geng et al., 2024). However, surface ozone (O₃) pollution has emerged as a growing concern. From 2015 to 2022, the number of O₃ pollution days increased steadily in major cities such as Beijing, Shanghai, and Guangzhou (Li et al., 2019; Wang et al., 2023), with exceedance days more than doubling in some regions (Ozone Pollution Control Committee of Chinese Society of Environmental Sciences, 2024). In response, the “Opinions on Deepening the Fight Against Pollution”, issued by the Central Committee of the Communist Party of China and the State Council, incorporated coordinated control of both PM_{2.5} and O₃ into the “14th Five-Year Plan” (2021–2025), marking a strategic shift toward multi-pollutant management.

Tropospheric O₃ is a secondary pollutant formed through photochemical reactions involving volatile organic compounds (VOCs) and nitrogen oxides (NO_x). It consists of two components: locally produced O₃ from anthropogenic emissions and background O₃, both of which impact human health, ecological ecosystems, and agricultural productivity (McDonald-Buller et al., 2011; Wang et al., 2009b). Background O₃ refers to the O₃ concentration present in the absence of local anthropogenic precursor emissions. It originates from a variety of natural and non-local processes, including methane (CH₄) oxidation, stratosphere–troposphere exchange (STE), vegetation, soil, lightning, wildfires and long-range pollutants transport, as shown in Fig. 1 (Dolwick et al., 2015; Thompson, 2019). Among these sources, CH₄ is unique due to its long atmospheric lifetime (8–9 years) and globally well-mixed distribution (Fiore et al., 2002b; Vingarzan, 2004; West and Fiore, 2005; Thompson, 2019). In the pre-industrial era (~1750), natural CH₄ sources (e.g., wetlands, inland waters, geological emissions) contributed ~95% of global emissions (Lassey et al., 2000; Prather et al., 2012; Valdes et al., 2005), making CH₄ oxidation a stable background contributor to tropospheric O₃ (Skipper et al., 2021; Sun et al., 2024; Thompson, 2019; Vingarzan, 2004; Wu et al., 2008). However, over the past century, anthropogenic CH₄ emissions from agriculture, fossil fuels, and waste have increased substantially, accounting for over 60% of global CH₄ by 2012 (Fiore et al., 2002b; Jackson et al., 2024; Kirschke et al., 2013; Lelieveld et al., 1998; Saunio et al., 2016). This transition challenges the traditional classification

of CH₄-driven O₃ as part of the “background,” and calls for a more precise attribution that excludes anthropogenic CH₄ from background O₃ estimates. Differentiating natural from anthropogenic CH₄ contributions is thus crucial for improving the accuracy and policy relevance of background O₃ assessments.

Background O₃ typically contributes 60–80% of total tropospheric O₃ at both global and regional scales (Akimoto et al., 2015; Chen et al., 2022; Dolwick et al., 2015; Lee and Park, 2022; Lefohn et al., 2014; Zhang et al., 2011). Unlike PM_{2.5}, which can be more directly mitigated through local emission reductions, O₃ management is more complex due to its nonlinearity and the presence of a large, unmodifiable background component (Chen et al., 2022). Although emission control measures in Europe, the United States (U.S.), and Japan have reduced O₃ exceedances, background O₃ levels have continued to rise (Akimoto et al., 2015; Cooper et al., 2012; Wilson et al., 2012; Yan et al., 2021). For example, in the U.S., the relative contribution of background O₃ to total ground-level O₃ has risen by approximately 6% over the past two decades (Jaffe et al., 2018), driven by climate change, rising CH₄, and transboundary pollution (Chen et al., 2022; Vingarzan, 2004). This trend is especially concerning in East Asia, where background O₃ is further elevated by regional transport from neighboring countries, exacerbating the problem (Vingarzan, 2004). As anthropogenic NO_x and VOCs emissions decline under stricter regulations, the relative importance of background O₃ in shaping observed pollution will only increase (Jaffe et al., 2018; Lam and Cheung, 2022; Skipper et al., 2021), limiting the effectiveness of local controls and demanding new international and multi-scale mitigation strategies.

Background O₃ defines the “baseline” for regional O₃ pollution and sets the upper bound of achievable air quality improvements through domestic anthropogenic emission controls (Fiore et al., 2014; Wang et al., 2009a; Zhang et al., 2011). Persistently high background O₃ levels complicate compliance with current and future O₃ standards, a challenge recognized by major agencies such as the National Aeronautics and Space Administration (NASA) (Huang et al., 2015; Thompson, 2019; Vingarzan, 2004) and in China’s “Blue Book on Prevention and Control of Atmospheric Ozone Pollution” (Ozone Pollution Control Committee of Chinese Society of Environmental Sciences, 2022). Despite its importance, understanding of background O₃ remains constrained by inconsistent definitions, diverse

estimation methods, and limited regional assessments. While several recent reviews have touched on background O₃ in the broader context of O₃ pollution (Lu et al., 2019b; Liu et al., 2020; Sahu et al., 2021; Wang et al., 2022b; Xu, 2021), and a few studies have provided quantitative estimates and source apportionment of background O₃ in China (Sahu et al., 2021; Wang et al., 2022b; Chen et al., 2022; Wang et al., 2011), no dedicated, methodologically focused synthesis is available.

This study addresses that gap by: (i) systematically reviewing the evolution of the background O₃ concept; (ii) providing a comparative assessment of the methods (i.e., in situ measurement, statistical analysis, numerical modeling, and integrated methods) employed to estimate background O₃; and (iii) synthesizing the spatiotemporal patterns of background O₃ in China within a broader global context, examining the spatial and temporal variations of background O₃ across China using publicly available data. Finally, we identify key knowledge gaps and propose future research priorities to advance understanding and inform effective policy responses. As background O₃ increasingly shapes the O₃ landscape, this review provides timely insight into the scientific and regulatory frontiers of O₃ pollution control both in China and globally.

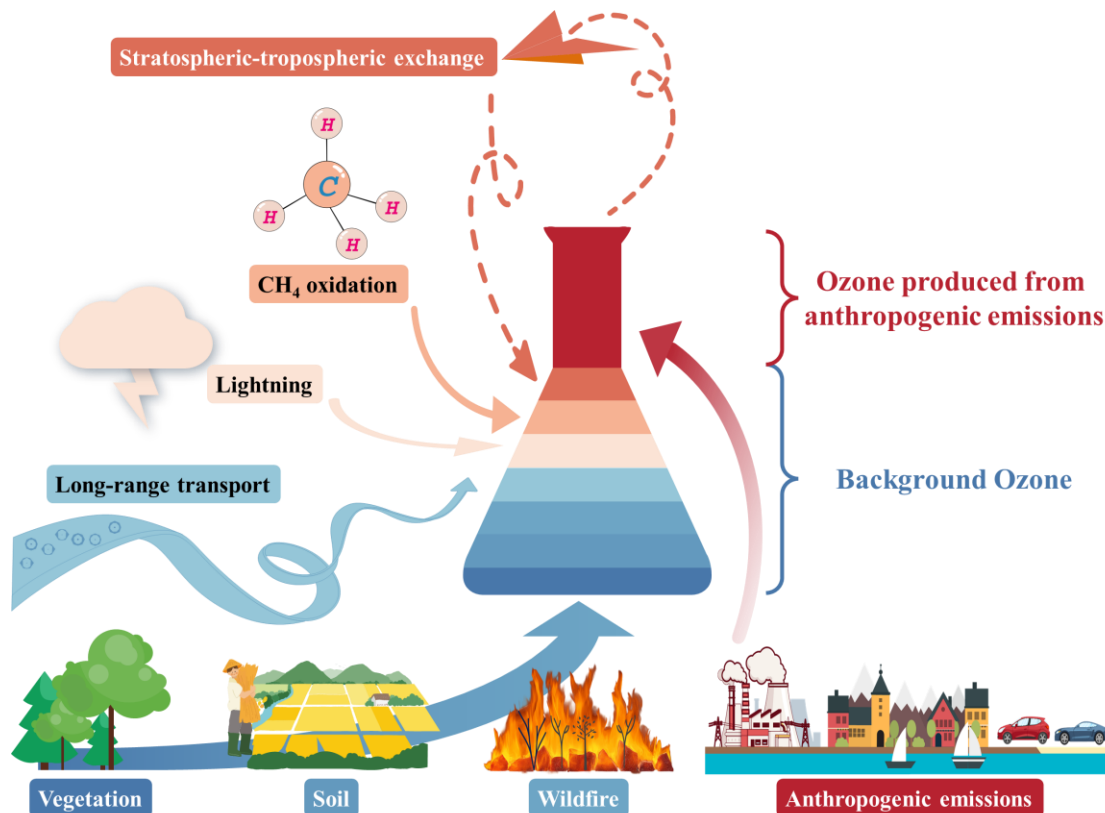


Figure 1: Conceptual diagram of tropospheric O₃ components and sources.

2 Materials and methods

2.1 Data source and study area

To provide a comprehensive synthesis of advancements in the study of background O₃, a systematic literature search was conducted across major academic databases, including the Web of Science, Google Scholar, Science Direct (Elsevier), Scopus, Springer, Wiley, and China National Knowledge Infrastructure (CNKI). The search was centered on the following key thematic terms: background/baseline/natural ozone/O₃, regional background ozone/O₃, and policy relevant background ozone/O₃, ensuring the inclusion of a wide range of relevant studies. This study identified 153 pertinent documents, comprising 132 peer-reviewed English-language papers, 10 peer-reviewed Chinese-language papers, 6 English-language reports, 1 English-language books, 2 Chinese-language books, and 2 Chinese-language master's theses. These documents form the core foundation of this review, which traces the evolution of the definition and estimation method for background O₃ over a span of seven decades (1952–2024), providing a comprehensive historical perspective on the development of the field.

In addition to reviewing the definition and estimation method for background O₃, we also analyzed the spatial and temporal characteristics of regional background O₃ concentrations in China during the period 1994–2020. This analysis was based on 44 peer-reviewed papers, including 28 papers in English and 16 papers in Chinese, which collectively provided over 700 data points on background O₃ concentration from various regions and time periods within China. To ensure the reliability and comparability of compiled background O₃ estimates, we adopted strict inclusion criteria: (i) reported values must specify temporal coverage and measurement or estimation methods; (ii) study location must be clearly identifiable within China; and (iii) data must originate from peer-reviewed publications, official reports, or other authoritative sources. All values considered in this study had already undergone rigorous quality control and screening by the original authors; therefore, no further outlier removal was performed. Where necessary, datasets were harmonized through standardized unit conversions and consistent temporal categorization to enhance comparability.

Based on these criteria and harmonization procedures, the final dataset integrates estimates across diverse temporal resolutions: annual data (31%, 235 data points), seasonal data (26%, 195 data points),

and monthly data (43%, 326 data points). The seasonal and monthly data were classified into spring (March–May; 24%, 127 data points), summer (June–August; 28%, 145 data points), autumn (September–November; 24%, 125 data points), and winter (December–February; 24%, 124 data points). A detailed breakdown of regional and temporal distributions is provided in Table S1. In addition, maximum daily 8-hour average (MDA8) O₃ concentrations for the seven regions during 2013 to 2018 were obtained from He et al. (2023).

To assess the regional differences in background O₃ concentrations across China, the country was categorized into seven geo-administrative regions based on a combination of social, natural, economic, and human environmental factors (He et al., 2023). These regions include Northeast China (NEC), North China (NC), East China (EC), Central China (CC), Northwest China (NWC), Southwest China (SWC), and South China (SC), as shown in Fig. 4. A detailed description of these regional divisions is provided in Table S2.

2.2 Data process

The background O₃ concentrations presented in this study are reported as volume mixing ratios in parts per billion (ppb). In some studies, however, values are expressed as mass concentration (μg m⁻³). To ensure consistency with international standards and comparability with global datasets, unit conversions were performed using Eq. (1):

$$ppb = \left(\frac{24.5 \text{ L mol}^{-1}}{48 \text{ g mol}^{-1}} \right) \times (\mu\text{g m}^{-3}), \quad (1)$$

Where 48 g mol⁻¹ is the molar mass of O₃ and 24.5 L mol⁻¹ is the molar volume of an ideal gas under the reference conditions of 25 °C and 1013.25 hPa, as specified in the 2018 amendment to China's Ambient Air Quality Standards (GB 3095–2012) issued by the Ministry of Ecology and Environment (https://www.mee.gov.cn/gkml/sthjbgw/sthjbgg/201808/t20180815_451398.htm). These reference conditions are consistent with international practices, such as 25 °C in the U.S. (U.S. EPA, 2011), 20 °C in the European Union (European Parliament and Council, 2008) and better reflect typical meteorological conditions across most regions of China.

2.3 Trend analysis

This study employed linear regression analysis to examine the annual trend in background O₃ concentration and assess the statistical significance of these trends over time. Specifically, linear regression was applied to the mean background O₃ concentrations (derived from scatter plot data) across different years, using the least squares method to determine the relationship between background O₃ concentration and time.

To evaluate the model's performance, the coefficient of determination (R^2) was calculated. R^2 represents the proportion of variance in background O₃ concentration explained by the linear model, indicating how well the model fits the observed data. Higher R^2 values suggest a strong fit, while lower values indicate a weaker fit. The P-value was also calculated to test the statistical significance of the linear relationship between background O₃ concentration and time. A smaller P-value (typically less than 0.05) indicates a statistically significant linear relationship, suggesting that the observed trend is unlikely to have occurred by chance. In contrast, larger P-values imply that the trend may not be statistically significant and could result from random variation.

It is important to note that, for the analysis of interannual variations in background O₃ concentration, only annual data from the compiled dataset were used. To ensure robustness, individual data points that deviated markedly from the overall regional trend were excluded, whereas consecutive deviations were retained to preserve temporal continuity. Here, "deviation" refers to values that differ substantially from most annual data within the aggregated regional dataset – likely reflecting spatial heterogeneity – rather than statistical outliers at the level of individual studies. In case where background O₃ concentrations were estimated using multiple methods within the same geographical region of a single study, the results were averaged to provide a more representative value.

3 Background ozone: conceptual evolution and key definitions

Background O₃ generally refers to the portion of O₃ concentrations that are not influenced by direct local anthropogenic emissions, though its definition varies across studies globally. In contemporary atmospheric research, background O₃ is commonly categorized into two distinct types: natural

background ozone (NBO) and regional background ozone (RBO). These two categories are crucial for understanding the sources and variations of background O₃ on both local and global scales. Figure 2 presents the historical evolution of background O₃ concepts, including their definitions and key characteristics.

Natural background ozone (NBO) is defined as tropospheric O₃ that exists in the complete absence of anthropogenic emissions, originating solely from natural processes (McDonald-Buller et al., 2011; Vingarzan, 2004; Wu et al., 2008). The primary sources of NBO include VOCs and NO_x emitted by natural sources such as vegetation, soil, lightning, wildfires, and the oxidation of CH₄, as well as O₃ exchange between the stratosphere and troposphere (Thompson, 2019). Historically, research into NBO originated with studies on atmospheric photochemistry. In the 1950s, investigations into photochemical smog in Los Angeles identified O₃ as a major component of smog, linking vehicular emissions of VOCs and NO_x to its formation (Haagen-Smit, 1952). While these studies primarily focused on anthropogenic sources, they also observed detectable O₃ concentrations in remote regions, far from urban pollution, suggesting natural processes contributed to O₃ production (Galbally et al., 1986; Volz and Kley, 1988). By the late 1970s, systematic studies in the U.S. identified key natural sources of O₃, such as biogenic VOCs (BVOCs), lightning, and soil-emitted NO_x, leading to the formation of the NBO concept (Crutzen, 1974; Jacob et al., 1999; Liu et al., 1987). Although NBO holds significant scientific importance, its practical application as a regulatory tool remains limited, particularly in the Northern Hemisphere, where anthropogenic emissions dominate regional O₃ production (Berlin et al., 2013). Nonetheless, NBO is a critical reference for establishing baseline O₃ levels globally, facilitating the evaluation of human contribution to atmospheric O₃ concentration.

In the 1990s, researchers in the U.S. began to recognize the critical role of long-range transport from anthropogenic sources in regional O₃ levels (Fiore et al., 2002a; Jacob et al., 1999; Vingarzan, 2004). This realization was pivotal in developing the concept of United States Background Ozone (USBO), which includes O₃ contributions from global NBO as well as anthropogenic emissions originating outside the country, such as from neighboring regions like Canada and Mexico (Skipper et al., 2021; Thompson, 2019). Acknowledging these external sources highlighted that background O₃ levels could not be fully

mitigated through domestic emission reductions alone.

By the early 21st century, research on background O₃ increasingly intersected with air quality policy development. A notable milestone was the introduction of Policy Relevant Background Ozone (PRBO) by the United States Environmental Protection Agency (EPA) in 2006 during revisions to the National Ambient Air Quality Standards (NAAQS) (U.S. EPA, 2006; Zhang et al., 2011). PRBO refers to ground-level O₃ concentrations that exclude all anthropogenic emissions from North America (the U.S., Canada and Mexico) while accounting for natural sources and long-range transport from anthropogenic and natural sources outside North America (Emery et al., 2012; Nopmongcol et al., 2016). This concept aimed to help policymakers assess the effectiveness of domestic control measures in reducing O₃ pollution and inform the establishment of stricter O₃ standards. By differentiating controllable from uncontrollable O₃ sources, PRBO enabled a more targeted approach to air quality management, framing policy discussions around the limitations of local pollution control in addressing O₃ levels (Duc et al., 2013; Zhang et al., 2011). The introduction of PRBO marked a significant transition in background O₃ research, shifting from a predominantly scientific focus to one directly informing air quality policy and regulatory frameworks (Hosseinpour et al., 2024; U.S. EPA, 2006, 2007).

Although USBO and PRBO share some common elements, their definitions differ primarily in geographic scope. PRBO focuses on transboundary contributions from regions outside North America, whereas USBO includes emissions from neighboring countries, such as Canada and Mexico, that affect the U.S. O₃ concentration. To address regional variations and better capture the dynamic of background O₃ in specific areas, advancements in atmospheric chemistry models have enabled scientists to differentiate the contributions of various sources to background O₃. This led to the emergence and widespread adoption of the term Regional Background Ozone (RBO) around the 2010s (Kemball-Cook et al., 2009; Langford et al., 2009; Ou-Yang et al., 2013). RBO refers to O₃ concentrations within a defined region that are unaffected by direct local anthropogenic emissions. Its main sources include natural emissions (e.g., BVOCs, soil, wildfires, and lightning), the oxidation of CH₄, stratosphere–troposphere exchange, and long-range transport (McDonald-Buller et al., 2011; Skipper et al., 2021; Sun et al., 2024; Wang et al., 2022a).

The distinction between NBO and RBO is crucial for understanding the complexity of background O_3 concentrations, as each reflects different sources and scales of influence. NBO represents a natural baseline, dominated by non-anthropogenic factors, serving as a reference point for assessing the human impact on atmospheric composition. In contrast, RBO reflects the interplay of natural and anthropogenic sources at local and global scales. Advancing our understanding of both NBO and RBO is essential for improving air quality models, refining emission control strategies, and establishing science-based standards for O_3 pollution reduction.

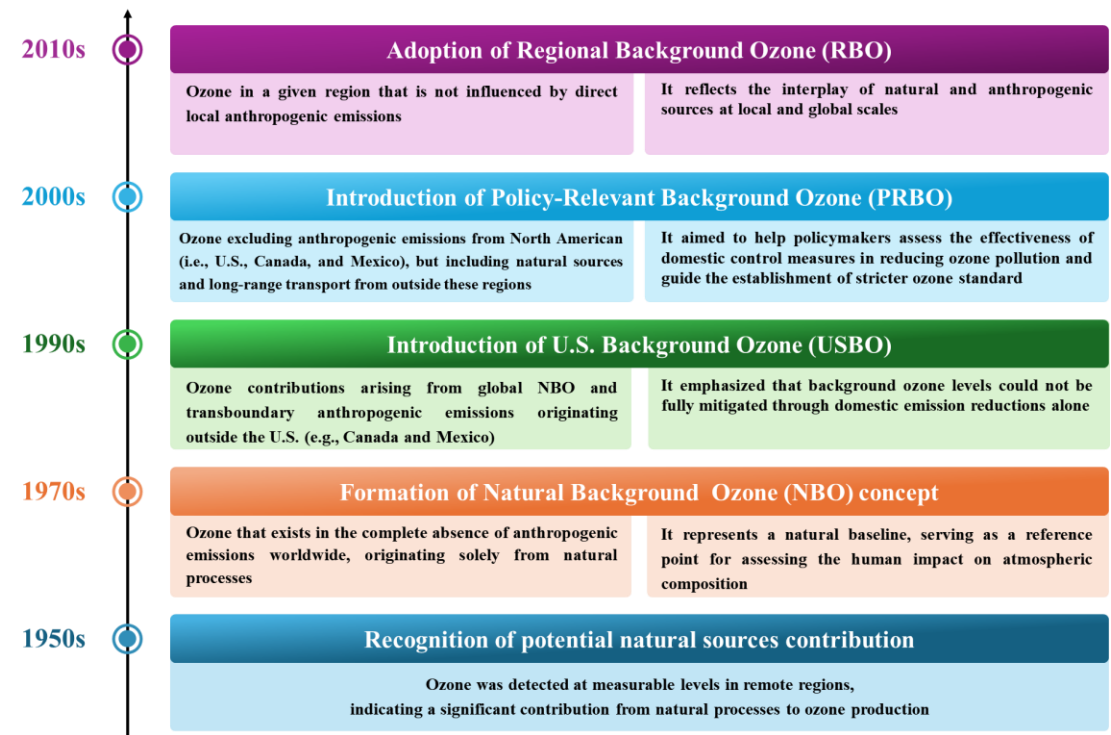


Figure 2: Historical evolution of background O_3 concepts: definitions (left box) and characteristics (right box).

4 Methods for estimating background ozone concentrations

The estimation of regional background O_3 is typically conducted using four primary methods: (1) in situ measurement estimation, (2) statistical analysis estimation, (3) numerical modeling estimation, and (4) integrated methods estimation. Figure 3 summarizes the advantages, limitations, and applicability of each method, providing a comparative overview of their respective strengths and weaknesses.

4.1 In situ measurement estimation

The in situ measurement estimation method involves the deployment of monitoring stations in remote or elevated areas, typically located far from direct pollution sources, to measure O₃ concentrations directly (Lam and Cheung, 2022; Wang et al., 2009b). This approach is widely recognized as one of the most direct and commonly used methods for estimating regional background O₃. It is relatively straightforward to implement, requires minimal post-measurement processing, and provides continuous, high frequency data on O₃ variations across spatial and temporal scales. These attributes render it an invaluable tool for tracking long-term trends in background O₃ concentrations.

However, this method has limitations, particularly concerning the spatial representativeness of the data. The limited number of monitoring stations, especially in regions with complex terrain or vast geographic areas, can result in insufficient coverage of the region's environmental conditions. Furthermore, measurements from background stations are subject to local meteorological conditions, such as temperature, humidity, and wind patterns, which can introduce uncertainties into background O₃ concentrations estimates (Skipper et al., 2021; Wu et al., 2017). This challenge is particularly pronounced in the Northern Hemisphere, where widespread anthropogenic emissions complicate the identification of truly “background” stations that are unaffected by human activities (Cooper et al., 2012; McDonald-Buller et al., 2011; Skipper et al., 2021; Vingarzan, 2004).

Despite its limitations, the in situ measurement estimation method remains an indispensable tool for estimating background O₃ concentrations. For instance, Vingarzan (2004) reported that background O₃ concentration in the Northern Hemisphere rose from approximately 10 ppb before the Industrial Revolution to 25–40 ppb by the 2000s, corresponding to an annual growth rate of 0.5–2%. Similarly, Akimoto et al. (2015) found background O₃ concentrations ranging from 60 to 70 ppb in Japan's Tokyo and Fukuoka metropolitan areas between 1990 and 2008. In southern China, Wang et al. (2009b) recorded background O₃ levels of 30–40 ppb at the Hok Tsui station in Hong Kong from 1994 to 2018, with an average annual increment of 0.58 ppb. These studies demonstrate that, despite challenges in achieving complete representativeness, the in situ measurement estimation method provides valuable insights into regional background O₃ trends and advances our understanding of the long-term impacts of both natural

and anthropogenic processes on atmospheric chemistry.

4.2 Statistical analysis estimation

The statistical analysis estimation method uses observed O₃ concentration data and applies statistical techniques to estimate regional background O₃ levels (Altshuller and Lefohn, 1996; Berlin et al., 2013; Steiner et al., 2010; Wang et al., 2022a). Historically, such estimations primarily relied on real-time measurements from monitoring stations. However, limitations in the spatial and temporal coverage of monitoring networks, along with their susceptibility to local environmental factors, have constrained their ability to capture the broader regional O₃ levels accurately. For example, monitoring stations situated in areas with complex terrain may yield skewed data due to topographical effects on air circulation patterns, which in turn significantly influence the distribution of O₃ concentration (Wang et al., 2022a). To overcome these challenges, researchers have increasingly adopted advanced statistical models that incorporate diverse observational data sources, enhancing the accuracy and reliability of background O₃ estimates (Riley et al., 2023; Rizos et al., 2022).

A notable advantage of statistical analysis estimation methods is their capability to process extensive datasets over long temporal scales, providing a cost-effective approach to estimating regional background O₃ levels. These methods can leverage large-scale data networks, such as satellite observations or regional monitoring systems (Langford et al., 2009). However, the reliability of statistical models is heavily dependent on the quality and spatial representativeness of the input observational data. High quality data are essential to minimize biases, and the monitoring stations must be strategically distributed to represent the target region adequately. Additionally, rigorous data preprocessing is critical to mitigate the influence of external factors, such as extreme weather events, that may distort the background O₃ concentrations estimates (Berlin et al., 2013; Langford et al., 2009).

The commonly used statistical analysis methods include the following:

4.2.1 Principal Component Analysis

Principal Component Analysis (PCA) is a widely used multivariate statistical technique designed to extract key patterns from datasets containing multiple interrelated variables (Jolliffe, 2005). By

transforming correlated variables into a smaller set of uncorrelated principal components, PCA effectively reduces data complexity while preserving the most significant information. In the context of atmospheric pollution, PCA has proven to be particularly useful for isolating background O₃ by minimizing the influences from meteorological factors, such as temperature, humidity, and wind, as well as local airflows from urban and industrial sources. This makes PCA an invaluable tool for understanding regional air quality and estimating background O₃ levels, particularly in cases where direct measurements are confounded by local pollution or short-term meteorological variability.

4.2.2 K-means clustering

K-means clustering is an unsupervised, iterative machine-learning algorithm widely employed for grouping data, such as O₃ concentrations, meteorological parameters, and other environmental factors, based on shared characteristics (Riley et al., 2023). Clusters with minimal anthropogenic influence are often interpreted as representative of background O₃ concentrations. These clusters, typically defined by low pollutant levels or specific meteorological conditions, facilitate the identification of periods or locations where regional background O₃ can be reliably assessed (Riley et al., 2023; Zohdirad et al., 2022).

4.2.3 TCEQ method

The Texas Commission on Environmental Quality (TCEQ) method, based on O₃ monitoring data from background regions, has been widely adopted in Texas, as a reliable approach for estimating regional background O₃ levels (Nielsen-Gammon et al., 2005). This approach defines regional background O₃ as the minimum value within maximum daily 8-hour average (MDA8) O₃ across all monitoring stations in a given area, effectively representing the lowest O₃ levels unaffected by local emissions (Wu et al., 2017). By focusing on these minimum values over an extended period, the TCEQ method isolates background concentrations, which are crucial for understanding regional air quality and evaluating long-term trends in O₃ pollution.

4.2.4 O₃-NO_x intercept method

The O_3 - NO_z intercept method is an approach for estimating background O_3 concentrations by establishing the linear relationship between O_3 concentrations and its precursors (Altshuller and Lefohn, 1996; Hirsch et al., 1996; Yan et al., 2021). In this approach, NO_z is defined as the difference between NO_y (the total reactive nitrogen species, including nitric acid and peroxy nitrates) and NO_x (which comprises NO and NO_2). NO_z serves as an indirect indicator of background O_3 level, based on the assumption that it reflects the presence of O_3 -producing precursors in the atmosphere. Through regression analysis, O_3 levels are extrapolated to the intercept where NO_z equals zero, representing an approximation of background O_3 concentrations unaffected by local emissions and photochemical influences.

However, Yan et al. (2021) noted that the method's accuracy could be compromised in areas with high rates of nitric acid (HNO_3) deposition. Elevated HNO_3 deposition sequesters reactive nitrogen compounds at the surface, potentially masking near-surface O_3 levels and leading to overestimations of background O_3 concentrations. To address these limitations, Yan et al. (2021) proposed a modified version of the O_3 - NO_z method, referred to as the $1-\sigma$ O_3 - NO_z method. This refinement involved excluding regions with high HNO_3 deposition rates and minimizing the influence of regional emissions through improved data selection criteria.

4.2.5 O_3 -CO-HCHO response method

Cheng et al. (2018) introduced an innovative approach for estimating background O_3 concentrations by using carbon monoxide (CO) and formaldehyde (HCHO) as chemical indicators to trace the production and consumption of O_3 . This method integrates the chemical reaction dynamics between O_3 , CO, and HCHO, resulting in a rapid-response O_3 estimator. This approach was specifically designed to enhance the efficiency and accuracy of O_3 estimation by leveraging the dynamic chemical processes that influence O_3 levels. Building upon this foundation, Yan et al. (2021) proposed the O_3 -CO-HCHO approach, which refines the original concept by eliminating the influence of both anthropogenic and natural emissions of O_3 precursors, enabling a more accurate estimation of background O_3 concentrations.

The O_3 -CO-HCHO method is particularly advantageous due to its applicability to both observational data and model outputs, offering robust results for regions with high isoprene emissions.

The method is governed by the following key equations:

$$O_3 = k_1(CO_{total} - CO_{back}) - (k_1k_2 - k_3)(HCHO_{total} - HCHO_{back}) + O_{3back}, \quad (2)$$

$$O_{3back} = O_3 - k_1(CO_{total} - CO_{back}) + (k_1k_2 - k_3)(HCHO_{total} - HCHO_{back}), \quad (3)$$

Here, $k_1 = \frac{\Delta O_3}{\Delta CO_{anthro}}$, $k_2 = \frac{\Delta CO_{bio}}{\Delta HCHO_{bio}}$, $k_3 = \frac{\Delta O_3}{\Delta HCHO_{bio}}$. The terms “anthro”, “bio”, “total”, and “back” refer to anthropogenic sources, biogenic sources, total sources, and background sources, respectively.

4.2.6 Percentile method

The percentile method is a widely adopted statistical approach for estimating regional background O_3 concentrations, offering a straightforward and practical alternative to complex modeling techniques (Berlin et al., 2013; Jenkin, 2008). This method involves analyzing O_3 concentration data over a specific time period and selecting a particular percentile to represent the background O_3 levels. The selected percentile is assumed to reflect minimal O_3 concentrations that are largely unaffected by local pollution sources, thereby serving as a proxy for regional background O_3 concentrations.

4.2.7 Temperature-ozone relationship method

The temperature-ozone relationship method estimates background O_3 contributions by analyzing the correlation between O_3 concentrations and temperature (Mahmud et al., 2008). Generally, O_3 concentrations increase with rising temperatures, as elevated temperatures enhance the photochemical reactions that produce O_3 . However, within a specific temperature range, O_3 concentrations tend to stabilize due to the equilibrium between O_3 production and destruction processes. These stabilized O_3 levels, typically observed during periods of relatively stable meteorological conditions, are often regarded as indicative of regional background O_3 concentrations, reflecting natural influence rather than anthropogenic emissions (Mahmud et al., 2008; Sillman and Samson, 1995; Steiner et al., 2010).

4.2.8 Nocturnal ozone concentration method

The nocturnal O_3 concentration method leverages the relatively stable O_3 levels observed during nighttime, when photochemical reactions driven by sunlight are absent, making it a valuable approach

for estimating regional background O₃ levels (Chan et al., 2003). At night, O₃ levels generally remain constant or exhibit minimal fluctuations, as they are primarily governed by the equilibrium between O₃ production and destruction through reactions with NO_x and other atmospheric components. However, this method is not without its challenges. A key limitation arises from the titration reaction between O₃ and NO, which produces NO₂ and depletes ambient O₃ levels. This phenomenon, known as O₃ titration, can result in underestimation of true background O₃ concentrations, particularly in areas with elevated NO emissions (Akimoto et al., 2015; Itano et al., 2007; Shin et al., 2012).

To mitigate the impact of O₃ titration, researchers have introduced adjustments to nocturnal O₃ estimates by incorporating a “total O₃” concentration, denoted as O_{3total}, which serves as a proxy for background O₃ levels. The “total O₃” is calculated using the following equations:

$$[O_{3total}] = [O_3] + [NO_2] - \alpha \times [NO_x], \quad (4)$$

Here, [O₃], [NO₂], and [NO_x] (= [NO] + [NO₂]) represent the mixing ratios of O₃, NO₂, and NO_x, respectively. The parameter α accounts for the fraction of NO₂ in NO_x from primary emissions, with a typical value of $\alpha = 0.1$ used in most studies (Akimoto et al., 2015; Itano et al., 2007; Shin et al., 2012). However, Wang et al. (2009b) suggested a lower value of $\alpha = 0.041$, introducing variability in the estimated [O_{3total}]. This adjustment helps to compensate for the effects of NO titration, yielding a more accurate representation of regional background O₃ levels.

Statistical analysis methods have been widely used to estimate regional background O₃ concentrations. For example, Langford et al. (2009) applied PCA to analyze regional background O₃ concentrations in Texas from August to October 2006. Their analysis revealed that the first principal component accounted for approximately 84% of the variance in the O₃ data, strongly indicating its relevance as a proxy for background O₃ levels. Riley et al. (2023) applied K-means clustering to estimate background O₃ concentrations in eastern Australia from 2017 to 2022. Their analysis revealed an average background O₃ concentration of 28.5 ppb, with a decadal increase of 1.8 ppb, reflecting the global trend of rising background O₃ levels. Berlin et al. (2013) and Langford et al. (2009) used TCEQ method to estimate background O₃ concentrations during high-O₃ periods (May–October) in Texas between 2000 and 2012. Their estimates ranged from 25 to 45 ppb and 40 to 80 ppb, respectively. Akimoto et al. (2015)

proposed using the 2nd percentile of MDA8 O₃ concentrations as a suitable measure of background O₃ levels in Japan, capturing low concentrations unaffected by local anthropogenic emissions during high-O₃ episodes. Chen et al. (2022) used **temperature-ozone relationship** method to assess background O₃ levels **of the region-specific** in China from 2013 to 2019, reporting concentrations of 35–40 ppb during clean seasons and 50–55 ppb during O₃-polluted seasons.

4.3 Numerical modeling estimation

The numerical modeling estimation method, which uses atmospheric chemistry and transport models such as GEOS-Chem, WRF-Chem, and CMAQ, is widely employed to simulate the formation, transportation, and variability of regional background O₃ concentrations. These models offer several distinct advantages by incorporating a comprehensive array of atmospheric processes, including photochemical reactions, vertical mixing, advection, and the transport of pollutants across various spatial and temporal scales. By accounting for the intricate interactions among emissions, meteorological conditions, and atmospheric chemistry, numerical models provide a more robust and accurate representation of regional background O₃ levels compared to in situ measurement estimation or statistical analysis estimation methods alone. Additionally, numerical models can be customized to align with specific research objectives through adjustments to chemical mechanisms and parameterization schemes, rendering them adaptable to diverse regions and temporal scales.

A notable strength of numerical models lies in their ability to differentiate the contributions of various emission sources to regional O₃ concentrations (Jaffe et al., 2018; Thompson, 2019; Zhang et al., 2011). This capability sets them apart from in situ measurement estimation and statistical analysis estimation approaches, which typically lack the granularity to isolate the relative contributions of natural versus anthropogenic emissions. However, numerical modeling estimation also presents significant challenges. These models are computationally intensive, requiring substantial resources, especially when simulating extensive domains or prolonged time periods. Moreover, their accuracy depends heavily on the quality of input data, such as emission inventories, meteorological conditions, and assumptions regarding physical and chemical processes, which can introduce uncertainties in estimated O₃ concentrations (Dolwick et al., 2015; Guo et al., 2018; Hogrefe et al., 2018; Jaffe et al., 2018).

Numerical models typically estimate regional background O₃ concentrations using two primary approaches: the emission scenario method and the tracer method (Fiore et al., 2002a). The emission scenario method employs three-dimensional air quality models, such as GEOS-Chem, MOZART, WRF-Chem, and CMAQ, to simulate background O₃ levels by conducting perturbation experiments where local anthropogenic emissions are reduced or set to predefined values. This approach enables the isolation of local emissions' contributions to regional background O₃ levels (Zhang et al., 2011; Li et al., 2018; Lu et al., 2019a; Pfister et al., 2013). In contrast, the tracer method uses chemical tracers to track the transport and transformation of emissions, offering an alternative approach to estimating background O₃ concentrations. Models such as CMAQ-ISAM and CAMx-OSAT, developed by the U.S. Environmental Protection Agency (EPA), incorporate tracer methods to estimate regional background O₃ concentrations (Lefohn et al., 2014; Li et al., 2012; Reid et al., 2008).

Although both methods have their strengths, studies have highlighted discrepancies in O₃ estimates depending on the approach employed (Jaffe et al., 2018; Skipper et al., 2021). For example, Emery et al. (2012) found that the CAMx model generally produced higher background O₃ concentrations in the U.S. compared to GEOS-Chem, with CAMx showing a higher correlation with observational data, especially at remote stations and during high-O₃ episodes. Conversely, GEOS-Chem demonstrated greater accuracy in capturing seasonal mean O₃ concentrations in rural areas. Similarly, Dolwick et al. (2015) compared the tracer and emission scenario methods using CAMx and CMAQ models. Their analysis revealed consistent estimates of background O₃ concentrations in suburban U.S. areas across both methods. However, in urban areas, the tracer method yielded lower background O₃ estimates than the emission scenario method, indicating a substantial influence of local emissions on O₃ concentrations in densely populated regions. Equally, Fiore et al. (2014) reported differences in background O₃ concentrations between GEOS-Chem and GFDL-AM3 models, with variations ranging from 1 to 10 ppb depending on region, season, and altitude.

Numerical modeling estimation has been extensively applied to estimate global and regional background O₃ concentrations. For example, using the global model GEOS-Chem, Emery et al. (2012) and Zhang et al. (2011) estimated average background O₃ concentration in the U.S. from March to August

2006, ranging from 20 to 45 ppb, with 27 ± 8 ppb in low-altitude areas and 40 ± 7 ppb in high-altitude areas. Guo et al. (2018) reported annual variation of up to 15 ppb in regional background O₃ concentration in the **U.S.** between June and August from 2004 to 2012. Meanwhile, regional models such as CAMx and CMAQ yielded background O₃ estimates of 25 to 50 ppb in the **U.S.** between March and August 2006 (Emery et al., 2012). In China, Sahu et al. (2021) found background O₃ concentrations exceeded 22 ppb in 2015.

4.4 Integrated methods estimation

The three methods discussed above each possess distinct advantages and limitations, contributing to uncertainties in estimating regional background O₃ concentration. Given these challenges, researchers have increasingly turned to integrated methods to improve the accuracy and reliability of these estimations.

For instance, Dolwick et al. (2015) improved model-based estimates of background O₃ by comparing observed and simulated O₃ concentrations. Their analysis of rural areas in the western **U.S.** during April to October 2007 reported background O₃ concentrations ranging from 40 to 45 ppb, with the lowest concentrations observed along the Pacific coast, ranging from 25 to 35 ppb.

Similarly, Sun et al. (2024) refined estimates by treating model biases as spatial functions, optimizing regional background O₃ estimations. Based on this methodology, Skipper et al. (2021) extended the methodology by incorporating both spatial and temporal functions to account for variations driven by regional background O₃ and anthropogenic emissions. This revised approach estimated an average background O₃ concentration of approximately 33 ppb for the **U.S.** in 2017, with peak values around 38 ppb. Notably, this adjustment improved the consistency of estimates by 28% compared to the unadjusted model, demonstrating the utility of integrated methods in refining atmospheric models.

The rapid advancement of machine learning (ML) techniques has further facilitated the integration of these technologies with traditional methods for estimating regional background O₃ concentrations. For example, Hosseinpour et al. (2024) developed a multivariate linear regression (MVLR) model and a random forest (RF) based ML algorithm to adjust model-derived background O₃ concentrations. While the MVLR model follows an adjustment method akin to that of Skipper et al. (2021), the RF-ML

algorithm employs the Shapley Additive Explanations (SHAP) method to evaluate the relative importance of each input variable. The RF-ML model, trained using k-fold cross-validation, demonstrated superior predictive accuracy. Hosseinpour et al. (2024) showed that the RF-ML algorithm produced results most consistent with those from the in situ measurement estimation method, outperforming those from the original CAMx model, MVLR adjustments, and two other ML algorithms. Utilizing this methodology, they estimated background O₃ concentrations in 13 urban areas of the U.S. during April–June and July–September 2016 to range from 31–46 ppb and 27–45 ppb, respectively. This finding underscores the potential of ML algorithms to enhance model-based background O₃ estimates by capturing nonlinear relationships and complex variable interactions (Breiman, 2001; Kashinath et al., 2021).

Overall, integrated methods, particularly those integrated with machine learning techniques, represent a significant advancement in estimating regional background O₃ concentrations. These approaches not only improve the accuracy and robustness of estimates but also provide valuable insights into the complex dynamics of O₃ formation and transport. By combining observational data, statistical adjustments, and advanced modeling techniques, researchers can achieve a more comprehensive understanding of regional O₃ levels and their temporal variations.

Method	Advantages	Limitations	Applicability
 In situ measurement	• direct observation • reliable data • high temporal resolution	• limited spatial coverage • difficult to fully exclude human impact	remote areas with low human impact
 Statistical analysis	• capable of handling large-scale data • low computational cost	• rely on model assumptions and data quality • limited regional applicability	trend analysis
 Numerical modeling	• source- and process-resolved	• high computational cost • rely on model accuracy • inherent uncertainties	large-scale regions
 Integrated methods	• combines strengths of multiple methods • improved accuracy and reliability	• technical complexity • lack of standardization interregional inconsistencies	high-precision assessments and policy-relevant applications

Figure 3: Summary of the advantages, limitations, and applicability of different estimation methods for background O₃.

5 Comprehensive assessments of background ozone in China: patterns, trends, sources, and global comparisons

5.1 Regional patterns of background ozone in China

Figure 4 presents the average background O₃ concentrations across various regions in China. On a national scale, the average background O₃ concentration is 41.4 ± 12.2 ppb, accounting for 79% of the MDA8 O₃ concentration. Notable regional variability in background O₃ concentrations is observed, highlighting the differential impacts of local meteorological conditions, pollutant emissions, and geographic characteristics.

Among the regions, Northwest China (NWC) stands out with the highest background O₃ concentrations, reaching 48.2 ± 8.3 ppb, which accounts for 96% of the MDA8 O₃ concentration. This elevated concentration is attributed to several interrelated factors. First, strong solar radiation and arid atmospheric conditions enhance photochemical reactions, accelerating O₃ formation. He et al. (2021) demonstrated that abundant sunshine and dry conditions significantly increase O₃ production due to the intensified photolysis of precursor compounds. Furthermore, the high altitude and unique surface characteristics of Northwest China (NWC) promote strong daytime atmospheric convection, facilitating the downward transport of O₃ from the upper atmosphere to the surface levels (Ding and Wang, 2006; Liu et al., 2019; Ma et al., 2005; Nie et al., 2004). Additionally, the relatively low anthropogenic emissions result in fewer precursors like NO_x and VOCs, thereby minimizing rapid fluctuations in O₃ levels. The weaker nocturnal O₃ depletion, caused by limited O₃ scavenging from sparse emissions and lower nighttime temperatures, further amplifies baseline O₃ concentrations (Nie et al., 2004; Qin et al., 2023; Xu et al., 2020).

The urban clusters of North China (NC) and East China (EC), along with Southwest China (SWC), also exhibit higher background O₃ concentrations, averaging 40.3 ± 14.9 ppb, 39.0 ± 13.4 ppb, and 38.4 ± 10.4 ppb, respectively. These concentrations account for 75%, 67%, and 83% of the MDA8 O₃ concentration in each respective region. East China (EC) and North China (NC) are heavily influenced by high industrial and vehicular emissions, which release significant quantities of NO_x and VOCs. The precursors undergo photochemical reactions under intense sunlight and elevated summer temperatures,

resulting in higher O₃ levels. Moreover, the East Asian Summer Monsoon (EASM) facilitates the transport of O₃ and its precursors from low-latitude regions, such as South China (SC), to higher latitudes, exacerbating O₃ pollution during the monsoon season (Gao et al., 2005; Liu et al., 2019, 2021; Sun et al., 2016; Xu et al., 2011, 2020). In contrast, in Southwest China (SWC), regional pollutant transport plays a significant role. During spring, prevailing winds carry pollutants such as NO_x and VOCs from Southeast Asia, intensifying local O₃ levels (Ye et al., 2024). Summer conditions – characterized by high humidity, elevated temperatures, and intense solar radiation – further amplify photochemical O₃ formation (Chen, 2020). The region's complex topography, including mountainous areas and plateaus, also contributes to localized O₃ accumulation. For instance, the Sichuan Basin, with its basin-like terrain, impedes air mass dispersion, leading to pollutants entrapment and prolonged O₃ buildup (Hu et al., 2019).

The background O₃ concentrations in South China (SC), Central China (CC), and Northeast China (NEC) are relatively low compared to other regions of China, with values of 37.0 ± 8.9 ppb, 35.1 ± 12.6 ppb, and 33.1 ± 5.7 ppb, respectively. These concentrations account for 74%, 60%, and 68% of the MDA8 O₃ in each corresponding region. In South China (SC), the relatively low background O₃ concentrations can be primarily attributed to the frequent rainfall and high humidity, which facilitate the removal of O₃ precursors such as NO_x and VOCs, thereby suppressing O₃ formation (He et al., 2021). Although BVOCs emissions are relatively high in this region due to abundant vegetation and elevated temperatures, their impact on O₃ formation is less pronounced compared to regions like North China (NC). This is because anthropogenic emissions, such as vehicular exhaust and industrial discharges, typically amplify the contribution of BVOCs to O₃ formation. In the absence of significant anthropogenic pollution, the role of BVOCs in O₃ formation remains relatively limited (Ye et al., 2024).

In Central China (CC), the lower background O₃ concentrations are linked to the region's inland locations, which reduce its exposure to oceanic influences and transboundary pollutant transport. The absence of strong maritime airflow limits the import of O₃ precursors, while frequent rainfall during the warmer months helps remove these precursors from the atmosphere, further suppressing O₃ formation (Sahu et al., 2021; Ma et al., 2024). Anthropogenic emissions, primarily from vehicular exhaust, industrial discharges, and solvent usage, constitute the dominant sources of O₃ in this region (Zeng et al., 2018).

Consequently, the relative contribution of background O₃ is lower, as anthropogenic emissions play a more substantial role in O₃ formation. In Northeast China (NEC), the lower background O₃ concentration can be attributed to a prolonged period of low temperature, which significantly reduces the rate of photochemical reaction. Additionally, the region experiences strong summer air convection and substantial precipitation, both of which further inhibit O₃ generation (Chen, 2024; Xu et al., 2020).

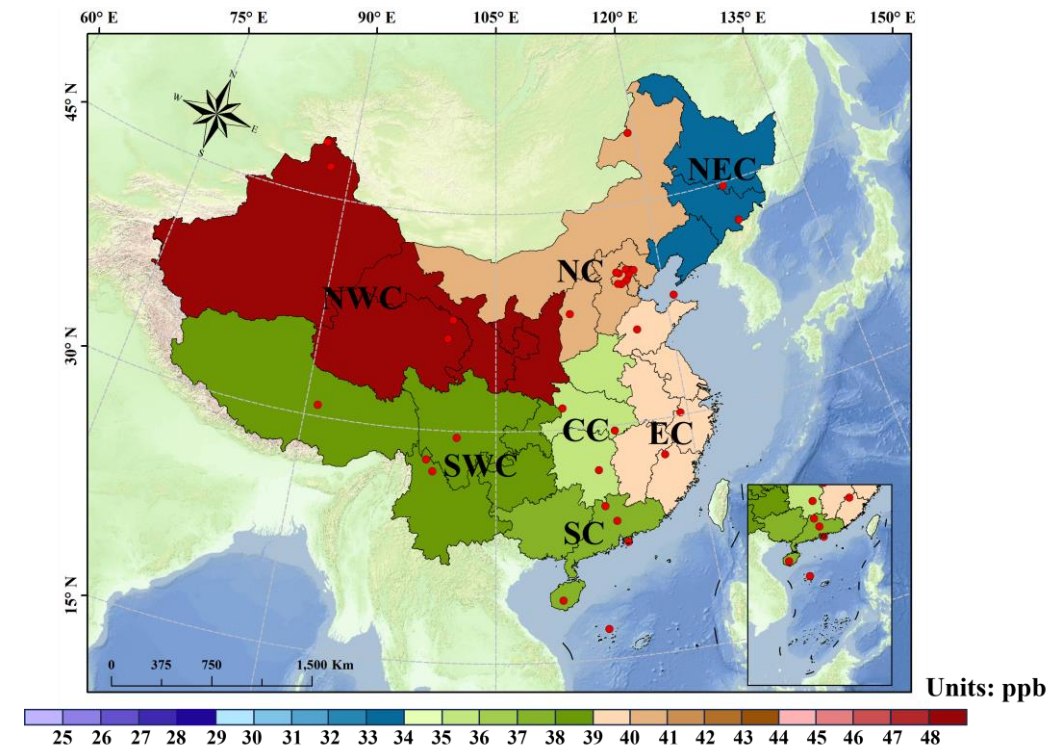


Figure 4: Spatial distribution of background O₃ concentrations (1994–2020) across various regions of China. The locations of 33 background monitoring stations are indicated with red dots. The seven regions include Northeast China (NEC), North China (NC), East China (EC), Central China (CC), Northwest China (NWC), Southwest China (SWC), and South China (SC).

5.2 Comparative evaluation of background ozone concentration estimates using diverse methods

Figure 5 presents a comparative assessment of background O₃ concentrations estimates in China from four common approaches: in situ measurement, statistical analysis, numerical modeling, and integrated methods. Among these, in situ measurement estimation method remains the most widely applied, supported by extensive datasets from 33 background monitoring sites (n = 678; Fig. 4, Table S3). By contrast, integrated methods have only recently emerged and have been applied in a limited number of case (n=8), reflecting their greater methodological complexity and reliance on comprehensive data

integration.

National mean background O₃ concentrations estimated by different methods are broadly comparable but show notable differences. In situ measurement estimation method (41.7 ± 12.3 ppb) and statistical analysis estimation method (39.9 ± 11.3 ppb) yield the highest values, followed by numerical modeling estimation method (37.4 ± 11.9 ppb). Integrated methods yield the lowest values of 34.5 ± 1.6 ppb, approximately 6 ppb lower than those from in situ measurement estimation and statistical analysis estimation method.

Despite similar mean values, the variability across methods is substantial. In situ measurement estimation reveals a particularly wide variability, with estimated background O₃ concentrations ranging from approximately 14 ppb to as high as 85 ppb. This broad range reflects the substantial influence of localized factors, such as topography, climatic conditions, and anthropogenic emissions, on observational data. In comparison, statistical analysis estimation and numerical modeling estimation methods yield relatively consistent results, although the difference between the maximum and minimum estimated background O₃ concentration for both methods reaches 60 ppb. Notably, more than 80% of the estimated background O₃ concentrations fall within the range of 25–53 ppb, suggesting a reasonable degree of agreement between the two methods. The consistency is likely attributable to the reliance on long-term data trends and calibrated algorithms, which effectively reduce the impact of extreme values while capturing broader patterns in O₃ behavior.

In contrast, the integrated methods – combining in situ observation, statistical analysis, and numerical results – yield the narrowest range (32–37 ppb), with the value of 34.5 ± 1.6 ppb. This narrow range reflects their strength in reconciling model consistency with real-world variability, rather than oversimplification. By harmonizing data sources, integrated methods reduce methodological noise and yield more robust, policy-relevant estimates. The limited number of applications, however, may also contribute to the observed low variability. Although studies in China remain scarce, international applications underscore their potential. For instance, Skipper et al. (2021) showed that incorporating spatial and temporal bias corrections improved the consistency of model-derived background O₃ estimates by 28% relative to unadjusted models. Similarly, Hosseinpour et al. (2024) demonstrated that

a random forest machine learning (RF-ML) algorithm integrating multiple data sources with nonlinear feature analysis produced background O₃ estimates most consistent with in situ observations for correcting air quality model simulations and outperformed the original CAMx model, multivariate regression, and other ML algorithms. Collectively, these studies highlight the value of integrated methods in producing consistent estimates, particularly for regulatory applications and long-term trend assessments. Nevertheless, further validation is needed to determine whether the observed low variability reflects true methodological robustness or limited sampling. Importantly, no single method is definitive. Each carries inherent assumptions. Integrated methods therefore provide a complementary framework that balances empirical realism with generalizability.

Method-dependent discrepancies underscore the complexity of estimating background O₃. Variability arises from differences in input data, model assumptions, and the parameterization of physical and chemical processes (Jaffe et al., 2018; Skipper et al., 2021; Wang et al., 2022a; Yan et al., 2021). For instance, in situ measurement estimation method is directly influenced by local meteorological and emission conditions, whereas the numerical modeling estimation method is subject to uncertainties in simulating processes such as natural emissions, transboundary transport, and photochemical reactions. Ideally, direct comparison of background O₃ estimates derived from multiple methods at the same location would clarify their relative strengths and limitations. However, such comparison was not feasible here due to methodological and data constraints. First, the dataset used in this study is limited to China, where only a subset of the methods described in Sect. 4.2 has been applied, each requiring specific datasets and exhibiting region-dependent applicability. Second, background O₃ exhibits pronounced spatial and temporal variability, while existing studies often target different subregions and time periods, making consistent co-located comparisons impractical. Despite these challenges, several studies have conducted preliminary intercomparisons within the same region. In Shandong, Wang et al. (2022a) reported that PCA (using ambient O₃ alone) yielded background O₃ about 20 ppb higher than the TCEQ approach, with seasonal patterns more consistent with background-site observations. The TCEQ method tended to underestimate background O₃ because minimum MDA8 O₃ values were often influenced by residual urban emissions. In the inland southeastern U.S., Yan et al. (2021) found the O₃-CO-HCHO

method yielded the lowest estimates (10–15 ppb), the 1- σ O₃-NO_x method intermediated values (15–25 ppb), and the 5th percentile method the highest (20–30 ppb), likely due to anthropogenic influences in urban downwind regions. Likewise, Chen et al. (2022) revealed that the nocturnal O₃ method underestimated background O₃ by up to 30% compared with the temperature-ozone relationship method during polluted seasons in China.

Collectively, these studies demonstrate that methodological choices alone can lead to discrepancies of 10–20 ppb in background O₃ estimates within the same region. Careful interpretation therefore requires explicit attention to methodological assumptions, data representativeness, and sensitivity to emission influences. Moving forward, the development of harmonized datasets would enable the consistent application of multiple methods at the same regions and time periods, providing more robust intercomparisons and clearer insights into the strengths and limitations of each approach.

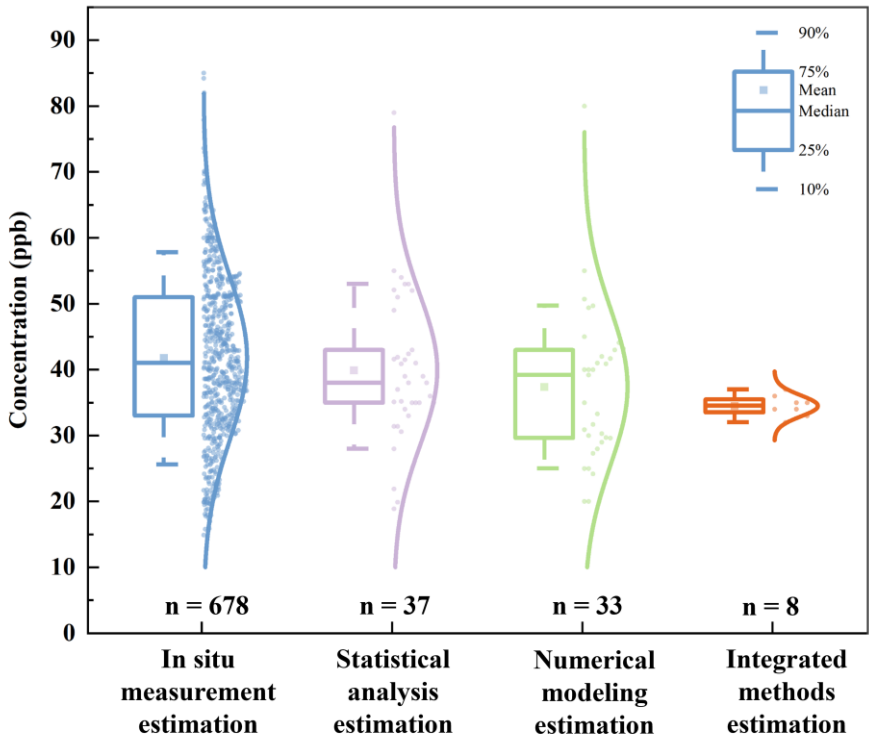


Figure 5: Estimated regional average background O₃ concentrations in China from 1994 to 2020 based on multiple methods. All data sources are compiled and summarized in Table S1. The values of “n =” below each box indicate the number of individual data records used in the analysis for each method category.

5.3 Long-term trends and interannual variability of background ozone in China

Due to the absence of long-term background O₃ records for other regions, Figure 6 focuses on the annual

variation trends of background O₃ concentrations in four regions of China – South China (SC), Northwest China (NWC), North China (NC), and East China (EC) – during the period from 1994 to 2020. Overall, background O₃ concentrations have exhibited an upward trend across these regions, though the magnitude and significance of the trends vary regionally.

South China (SC) exhibited the most pronounced increase, with an average growth rate of 0.36 ppb yr⁻¹ ($r^2=0.38$, $p<0.01$), as shown in Fig. 6(a). Although a modest decline has occurred since 2014, the long-term trend remains upward. This increase is likely driven by the regional transport of O₃ and its precursors. Previous studies suggest that rising background O₃ levels in Hong Kong are largely attributable to enhanced upwind emissions from mainland China and cross-boundary transport of precursors from Southeast Asia, particularly the Indochinese Peninsula (Wang et al., 2009b; Lee et al., 2014). Yang et al. (2019) further demonstrated that precursor emissions outside the Pearl River Delta region significantly contribute to local O₃ levels, with this influence intensifying in recent years.

Both Northwest China (NWC) and North China (NC) also exhibit substantial increases, with a growth rate of 0.32 ppb yr⁻¹ ($r^2=0.68$, $p<0.01$) and 0.31 ppb yr⁻¹ ($r^2=0.34$, $p<0.05$), respectively, as shown in Fig. 6(b) and Fig. 6(c). These trends are likely linked to enhanced stratosphere–troposphere exchange (STE) and the long-range transport of O₃ precursors, as previously reported (Xu et al., 2018; Zhang et al., 2020). Large-scale circulation shifts and more frequent STE events have further amplified background O₃ levels in these inland regions (Xu et al., 2016, 2020; Xue et al., 2011). Notably, for North China (NC), two separate trend lines are presented in Figure 6(c), reflecting methodological differences among studies: Ma et al. (2016) provided a long-term record using MDA8 O₃ concentrations filtered from in situ observations, while most other studies used hourly averages over shorter or discontinuous periods. Since MDA8 O₃-based estimates are inherently higher than hourly means, aggregating them would bias trend interpretation. Therefore, separate presentation ensures consistency. Furthermore, MDA8 O₃ records are scarce elsewhere (typically fewer than four data points), precluding dual-trend comparison. The results of Ma et al. (2016) also support the intensification of background O₃ pollution in North China (NC), reporting a much steeper growth rate of 1.35 ppb yr⁻¹ ($r^2 = 0.80$, $p < 0.01$) based on observations at the Shangdianzi regional background station. This suggests that both regional

emissions and conducive meteorological conditions have played synergistic roles in driving the escalation of background O₃ levels in North China (NC).

In contrast, East China (EC) exhibited the slowest increase in background O₃ concentration, with an average growth rate of 0.27 ppb yr⁻¹ that is not statistically significant ($p > 0.05$) (Fig. 6(d)). Several factors likely explain this muted growth (Liu et al., 2021; Xu et al., 2020; Zhang et al., 2020). First, East China (EC) was among the earliest regions in China to adopt coordinated NO_x and VOCs controls, notably under the “Atmospheric Ten Measures” (2013) and the “Blue Sky Protection Campaign” (2018), which likely curbed precursors increases. Second, the region’s dense urbanization and heavy industrialization complicates separation of background O₃ from local anthropogenic signals, potentially leading to underestimation of long-term growth. Third, meteorological conditions – higher relative humidity, more frequent precipitation, and weaker solar radiation – tend to suppress photochemical O₃ formation relative to drier, high-insolation regions such as North China (NC) and Northwest China (NWC). Taken together, these factors may explain why East China (EC) appears to be approaching a plateau phase in background O₃ levels, in contrast to the stronger upward trends observed in other regions.

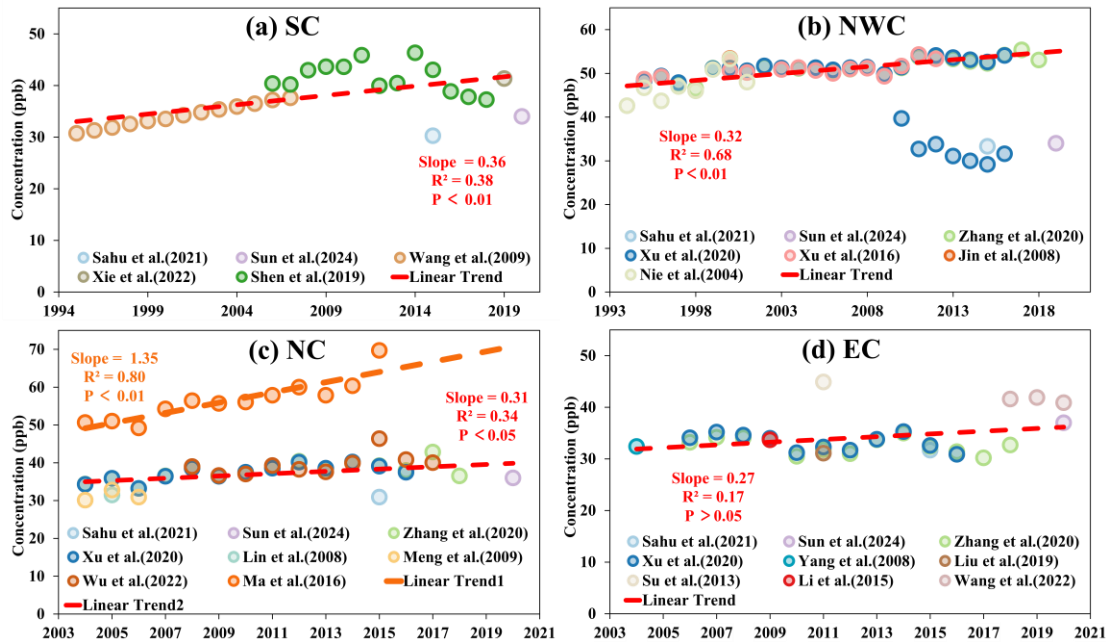


Figure 6: Annual trend of background O₃ concentrations in the SC regions (1995–2020), NWC (1994–2019), NC (2004–2020) and EC (2004–2020), estimated using multiple independent studies (detailed in Table S1). Dashed lines indicate linear regression based on available annual data points.

5.4 Seasonal variation of background ozone in China

Figure 7 illustrates the seasonal variations in mean background O₃ concentrations across China and its seven subregions during 1994–2020. Nationally, background O₃ exhibits pronounced seasonality, with comparable peaks in spring (47.2 ± 10.6 ppb) and summer (47.3 ± 15.4 ppb), and a pronounced minimum in winter (33.2 ± 9.8 ppb).

Regional patterns reveal clear differences in seasonal maxima. In Southwest China (SWC) and Northeast China (NEC), peaks occurred in spring (52.1 ± 9.9 ppb and 38.8 ± 4.4 ppb, respectively), largely driven by stratosphere–troposphere exchange (STE) and enhanced downward transport over elevated terrain, and also influenced by prevailing winds that transport NO_x and VOCs from Southeast Asia and other regions into these areas (Liu et al., 2019; Lu et al., 2019a; Xu et al., 2018; Wang et al., 2011; Ye et al., 2024). In contrast, North China (NC), Northwest China (NWC), and East China (EC) recorded summer maxima (56.8 ± 10.8 , 55.0 ± 8.5 , and 48.3 ± 16.9 ppb, respectively), consistent with the influence of the East Asian Summer Monsoon (EASM), which enhances precursor inflow and stimulates photochemical O₃ formation under high temperatures and intense solar radiation (Gao et al., 2005; Liu et al., 2019, 2021; He et al., 2021). South China (SC) and Central China (CC) reached their highest levels in autumn (46.9 ± 10.4 and 43.0 ± 14.2 ppb, respectively), likely reflecting inland pollutant transport by northeasterly winds combined with favorable sunlight conditions (Xie et al., 2022; Shen et al., 2019; Luo et al., 2019).

Seasonal minima also varied by region. Winter lows were observed in Northeast China (NEC, 24.5 ± 3.6 ppb), North China (NC, 24.9 ± 5.2 ppb), and East China (EC, 25.2 ± 8.1 ppb), reflecting weak photochemistry under low temperatures and reduced solar radiation. In contrast, South China (SC, 24.8 ± 5.0 ppb) and Central China (CC, 28.7 ± 10.0 ppb) exhibited summer minima, attributable to frequent precipitation and high humidity suppressing O₃ production. Southwest China (SWC) maintained persistently low levels in both summer (31.0 ± 8.2 ppb) and autumn (31.0 ± 4.6 ppb), whereas Northwest China (NWC) showed relatively lower concentrations in autumn (41.8 ± 8.9 ppb) and winter (41.9 ± 5.1 ppb).

In summary, the seasonal cycle of background O₃ in China is shaped by the interplay of regional

meteorology and precursor emissions, while vertical exchange and interregional transport further modulate seasonal peaks and troughs across regions.

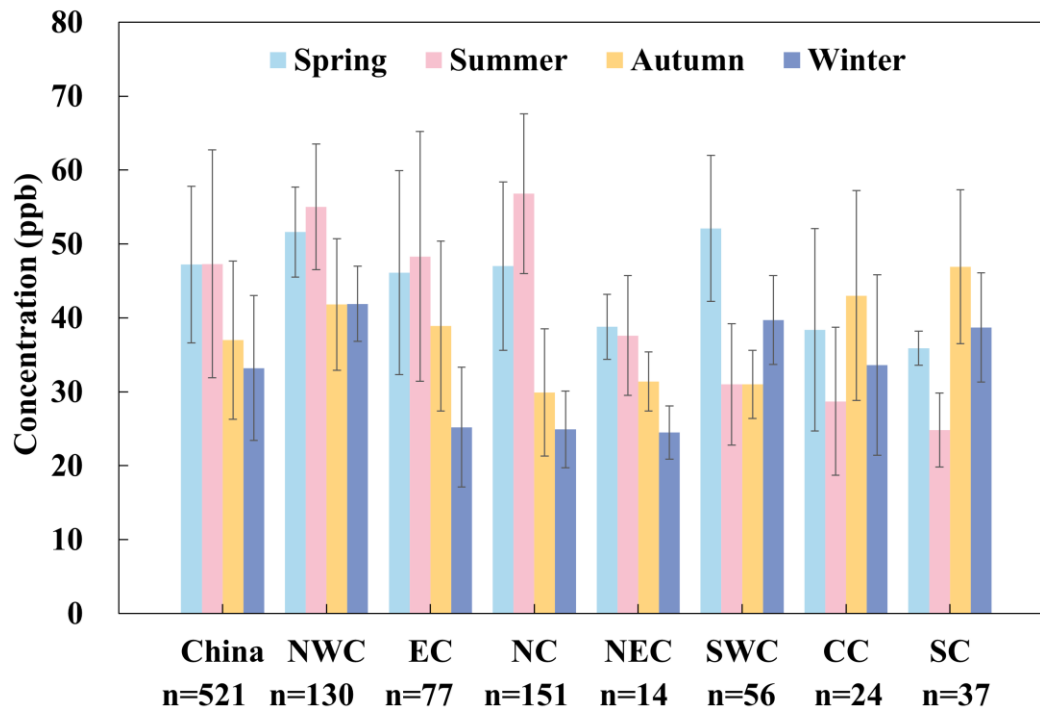


Figure 7: Seasonal variations in mean background O₃ concentrations across seven regions of China during 1994–2020. All data sources are compiled and summarized in Table S1. The values of “n =” indicate the number of individual data records or assembly estimates used in the analysis for each region and season.

5.5 Source attribution and analysis of background ozone in China

The analysis above reveals that the spatiotemporal variations of background O₃ are influenced by the synergistic effects of multiple factors, including regional natural source emissions, cross-regional transport, stratosphere–troposphere exchange, and local atmospheric pollutant reduction measures. These factors interact in complex and dynamic ways, resulting in significant regional and seasonal variations in background O₃ levels.

Natural source emissions are a key driver of background O₃ levels in China, with studies consistently highlighting their substantial contribution. For example, Wang et al. (2011) and Lu et al. (2019a), using the numerical model GEOS-Chem, estimated that over 70% of regional background O₃ concentrations in China originate from natural emissions, including BVOCs, soil NO_x, and CH₄ emissions and others. Among these, BVOCs exert a particularly significant impact on O₃ formation. Lu

et al. (2019a) demonstrated that during the peak summer months of July and August in 2016–2017, BVOCs emissions contributed over 15 ppb to the background O₃ in central and eastern China. Similarly, Chen et al. (2022) emphasized that during O₃ pollution seasons, BVOCs emissions dominate the increase in background O₃, contributing 8–16 ppb compared to non-pollution seasons. These findings underscore the importance of incorporating the variability of natural emissions into modeling and policy frameworks, particularly in light of future climate change that may exacerbate BVOCs emissions.

Long-range transport plays an equally significant role in shaping background O₃ concentration across China. Several studies have shown that the influx of O₃ and its precursors from other regions, including Southeast Asia, Europe, North America, India, and the Middle East, can elevate background O₃ concentration in China by 2–15 ppb (Han et al., 2019; Wang et al., 2011; Wang et al., 2022b; Li et al., 2014; Ni et al., 2018). This influence is particularly pronounced during specific seasons when atmospheric circulation facilitates the transboundary transport of atmospheric pollutants (Colombi et al., 2023; Ma et al., 2025; Ni et al., 2018; Sahu et al., 2021; Ye et al., 2024). Regional transport also significantly influences the background O₃ levels in urbanized and densely populated areas. For instance, Su et al. (2013) showed that air masses originating from high altitudes, the Yangtze River Delta region, and the Pearl River Delta regions could cause spikes at the Mount Wuyi background station, with concentration reaching 62–73 ppb, far exceeding the station’s annual average of 41 ± 15.9 ppb. Wang et al. (2022b) also found that emissions outside the Yangtze River Delta regions contributed as much as 63% to O₃ pollution within the region. Similarly, Wang et al. (2009b) measured that air masses from eastern China had an average O₃ concentration of 48 ppb at a background station in Hong Kong, highlighting the significant impact of inter-regional transport on coastal regions.

Stratosphere–troposphere exchange (STE) is a critical vertical transport process contributing to background O₃ levels, particularly in high-altitude and northern regions of China. This process is most active during spring, when stratospheric O₃ is transported downward into the troposphere (Ding and Wang, 2006; Lu et al., 2019a; Ma et al., 2025; Xu et al., 2018). Wang et al. (2011) estimated that STE contributes approximately 7 ppb to background O₃ concentrations in northern China during the spring season. Luo et al. (2024) further revealed that STE contributed an average of 9.6 ppb to surface O₃ over

the North China Plain during 19–20 May 2019. Observations at the Mt. Waliguan Station on the Tibetan Plateau further support the importance of STE; Xu et al. (2018) reported that STE contributes 8–12 ppb to background O₃ concentrations during spring. Lu et al. (2019a) found that STE processes contribute as much as 20 ppb to background O₃ concentration in western China during March and April, with an average contribution of 1.8–8.7 ppb across China from March to October. In lower-latitude regions such as the Pearl River Delta, Shen et al. (2019) demonstrated that vertical transport processes, including STE, predominantly influence background O₃ levels during spring and autumn. These findings underscore the critical role of altitude and latitude in modulating the magnitude of STE contributions.

5.6 Comparative analysis of background ozone levels: insights from China and global perspectives

Figure 8 presents a comparative analysis of background O₃ concentrations in China and several other global regions, with a particular focus on the U.S., Canada, Europe, Japan, and South Korea. On average, background O₃ concentrations in China (41.4 ± 12.2 ppb) are slightly higher than those observed in the U.S. (35.7 ± 14.0 ppb) (Chan and Vet, 2010; Dolwick et al., 2015; Emery et al., 2012; Fiore et al., 2003, 2002a; Hirsch et al., 1996; Parrish et al., 2009; Parrish and Ennis, 2019; Steiner et al., 2010; Vingarzan, 2004; Yan et al., 2021; Zhang et al., 2011) and Europe (34.2 ± 10.3 ppb) (Auvray and Bey, 2005; Brönnimann et al., 2000; Kalabokas et al., 2000; Naja et al., 2003; Parrish et al., 2009; Scheel et al., 1997; Vecchi and Valli, 1998; Vingarzan, 2004; Wilson et al., 2012). This suggests that although developed regions have made significant progress in controlling anthropogenic O₃ precursors, background O₃ remains a major concern due to various regional factors such as higher emissions, industrial activity, and specific atmospheric conditions (Huang et al., 2015). In contrast, background O₃ levels in China are significantly higher than those observed in Canada (26.9 ± 7.4 ppb) (Chan and Vet, 2010; Vingarzan, 2004), which is likely due to Canada's lower industrial activity, less dense population, and colder climate that limits the photochemical processes necessary for O₃ formation.

When comparing China to other East Asian regions, the background O₃ concentration is slightly higher than in South Korea (38.8 ± 11.74 ppb) (Ghim and Chang, 2000; Kim et al., 2023; Lam and Cheung, 2022; Lee and Park, 2022; Yeo and Kim, 2021), but marginally lower than in Japan (45.4 ± 23.2 ppb) (Akimoto et al., 2015; Lam and Cheung, 2022; Sunwoo et al., 1994; Tsutsumi et al., 1994). Detailed

information on the data, including a breakdown of regional and temporal distributions, is provided Table S4. Notably, East Asian regions, including China, South Korea, and Japan, typically exhibit background O₃ levels that are 3–20 ppb higher than those observed in Europe, the U.S., and Canada. This regional disparity is attributable to a combination of factors, including the region’s warm climate, high solar radiation, and the presence of industrialized areas that emit large quantities of O₃ precursors. These factors collectively enhance photochemical O₃ (Lee et al., 2021; Li et al., 2016; Nagashima et al., 2010; Yamaji et al., 2006). Furthermore, complex regional airflow patterns, including transboundary transport and local atmospheric dynamics, promote the accumulation of background O₃, especially in densely populated urban centers. These findings underscore the critical need for regional cooperation in addressing O₃ pollution in East Asia, where transboundary influences and shared atmospheric conditions complicate the management of background O₃ levels.

A more granular regional comparison reveals notable differences in background O₃ concentrations among various regions of both China and the U.S. Specifically, the difference in background O₃ concentrations between central and western China (including NWC and SWC) reaches 10 ppb, while the discrepancy between the Eastern and Western U.S. is as high as 13 ppb. Western China and the Western U.S. exhibit higher background O₃ levels. In particular, the Los Angeles area in the Western U.S. reports background O₃ levels as high as 62 ppb (Parrish and Ennis, 2019), a phenomenon attributed to the region’s combination of intense ultraviolet radiation, low humidity, and favorable atmospheric conditions for O₃ formation. Similarly, the higher altitudes of western China enhance its susceptibility to stratospheric transport, which contributes to elevated O₃ concentrations. The Western U.S. is similarly influenced by trans-Pacific atmospheric transport, further exacerbating O₃ levels.

In contrast to the significant regional differences observed in China and the U.S., background O₃ concentrations in Canada and Europe exhibit relatively small variations, typically ranging from 4 to 7 ppb. The limited variation in Canada can be attributed to factors such as its low population density, minimal industrial activity, and expansive natural vegetation, all of which, coupled with its cold climate, limit O₃ production. In Europe, the relatively smaller regional differences are likely as a result of effective transnational air quality management and stringent pollution control policies, which have successfully

minimized disparities in O₃ concentrations across the continent. The relatively uniform air quality management frameworks in these regions have helped mitigate large-scale emissions and reduce regional discrepancies in background O₃ levels (Miranda et al., 2015; Næss, 2004; Rodrigues et al., 2021; Xu et al., 2019).

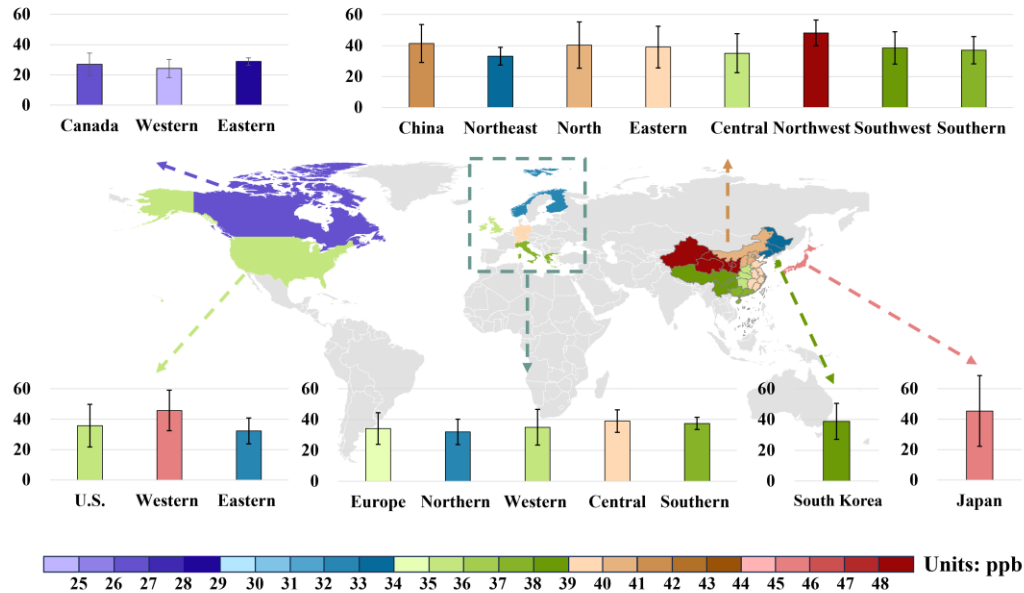


Figure 8: Average background O₃ concentrations in the U.S., Canada, Europe, South Korea, Japan, and China.

6 Conclusions and perspectives

Background O₃ concentrations are critical for understanding O₃ pollution, as they represent the baseline level of O₃ even in the absence of local anthropogenic emissions. These concentrations determine the maximum achievable reduction in O₃ through the mitigation of anthropogenic precursor emissions, making accurate estimates crucial for effective air quality management and setting realistic pollution control targets. This study provides a comprehensive review of the definition and estimation methods for background O₃ concentrations, with a focus on recent advances in regional research in China. Our findings reveal an average background O₃ concentration of 41.4 ± 12.2 ppb in China, which accounts for 79% of the tropospheric MDA8 O₃. Notable spatial variations are observed, with the highest levels in Northwest China (NWC, 48.2 ± 8.3 ppb) and the lowest in Northeast China (NEC, 33.1 ± 5.7 ppb), alongside an upward national trend reflecting growing O₃ pollution. Despite progress in estimation methods, discrepancies persist across the four estimation methods, with the in situ measurement

estimation method and statistical analysis estimation method yielding higher values, while the integrated methods offers lower but more consistent estimates. Compared to other regions, East Asia, including China, South Korea, and Japan, experiences background O₃ levels 3–20 ppb higher than the U.S., Canada, and Europe. This highlights the region-specific atmospheric conditions and pollution characteristics, and the imperative of addressing background O₃ pollution within a global framework.

Although substantial progress has been made in estimating background O₃ over recent decades, considerable challenges remain due to the complexity of its sources and the multitude of influencing factors, particularly in the context of global climate changes and transboundary pollution. Future research should prioritize several key areas to advance the understanding and management of background O₃:

6.1 Accurate quantification of background ozone sources and processes

Natural emissions, long-range transport, and stratosphere–troposphere exchange (STE) are key drivers of background O₃ concentrations; however, significant uncertainties remain in quantifying their individual contributions. To improve our understanding and predictive capabilities, future research must prioritize the refinement of quantification methods for these sources and processes. For instance, the variability of natural emissions, particularly from BVOCs and lightning, remains inadequately characterized across different climatic conditions. In addition, STE represents another critical but poorly understood source of background O₃, with studies indicating significant seasonal and regional variations in its contribution (Lu et al., 2019a; Xie et al., 2017). Despite the critical importance of these processes, existing models often encounter difficulties in accurately simulating natural emissions and STE, primarily due to limitations in model structures and parameterization (Auvray and Bey, 2005; Griffiths et al., 2021; Huang et al., 2024; Koo et al., 2010). As a result, the accuracy of model predictions for background O₃ concentrations is compromised, resulting in increased uncertainties that hinder effective policy planning and air quality management.

6.2 Development of integrated methods techniques

Single method approaches for estimating background O₃ concentrations have inherent limitations, as they often fail to capture the full spectrum of factors influencing O₃ levels. For example, while numerical

models provide valuable insights, they frequently underestimate actual O₃ concentrations due to simplifications in chemical processes and uncertainties in input data. In contrast, statistical analysis estimation methods are heavily dependent on the availability and representativeness of observational data, which can be sparse or biased, particularly in regions with limited monitoring networks. These limitations highlight the necessity for more integrated approaches that combine the strengths of different methods.

In this context, the development of integrated methods techniques presents a promising approach to improve background O₃ estimation. By integrating observational data, statistical analysis, and numerical results, integrated methods estimation can mitigate the inherent limitations of each individual method. For example, data assimilation techniques, which combine model outputs with real-time observational data, have been shown to improve both spatial and temporal resolution, yielding more accurate and robust O₃ estimates (Skipper et al., 2021; Sun et al., 2024). Additionally, the integration of high-resolution regional models with long-term observational datasets can significantly enhance spatiotemporal coverage of background O₃ estimates, enabling precise characterization of O₃ variability across diverse geographic scales, from urban centers to remote rural areas. Recent advancements in machine learning-based fusion methods further extend the potential of data integration by uncovering nonlinear relationships among multiple data sources, thereby improving estimation accuracy. These approaches can also account for complex interactions between meteorological conditions, emission sources, and atmospheric chemistry, which are often challenging to capture using traditional methods. Given the potential of integrated methods techniques to provide more accurate and comprehensive background O₃ estimates, future research should prioritize their continued development and validation. Such efforts will improve the precision and reliability of background O₃ estimates, thereby enhancing our understanding of regional O₃ pollution dynamics and supporting the development of more effective air quality management strategies.

6.3 Fostering international collaboration on long-range pollution transport

As air quality standards for O₃ become increasingly stringent, background O₃ concentrations have emerged as a critical challenge for many countries in achieving regulatory targets. This issue is

particularly pronounced in regions impacted by both local and transboundary pollution, where efforts to reduce domestic emissions may not fully address the underlying drivers of elevated background O₃ levels. For instance, studies conducted in the U.S. have demonstrated that despite substantial reductions in local emissions of O₃ precursors, background O₃ concentrations in some areas remain persistently high (Cooper et al., 2012; Huang et al., 2015). This phenomenon is partly attributed to long-range transport of pollutants, including O₃ precursors, from distant regions, often spanning international borders and even continents (Cynthia Lin et al., 2000; Dentener et al., 2010). Such transboundary pollution underscores the need for comprehensive international cooperation to effectively mitigate the challenges posed by background O₃.

International collaboration is therefore essential for tackling the elevated background O₃. To this end, fostering transboundary emission reduction agreements between countries and regions can play a pivotal role in curbing the long-range transport of O₃ and its precursors. Moreover, strengthening the global background O₃ monitoring network, particularly in remote regions and marine stations, would significantly enhance the capacity for real-time monitoring of background O₃ levels on a global scale.

6.4 Strengthening research on the interaction between background ozone and climate change

The impact of climate change on background O₃ concentrations represents a critical area for future research, with profound implications for air quality management and public health. Climate change is expected to affect background O₃ levels through multiple interconnected mechanisms. For example, rising temperatures and altered precipitation patterns are expected to affect natural emissions, such as BVOCs emissions from forests and NO_x emissions from soil, both of which are particularly sensitive to climatic factors like temperature and humidity. These changes would, in turn, influence regional background O₃ levels. Beyond these direct emission impacts, climate change is likely to modify atmospheric circulation patterns, thereby affecting the long-range transport of atmospheric pollutants and the spatial distribution of background O₃. Alterations in wind patterns and monsoon systems, for example, could significantly alter the transport of O₃ and its precursors over large distances, thereby exacerbating regional background O₃ levels, especially in areas downwind of major pollution sources (Collins et al., 2003; Sonwani et al., 2016; Sudo et al., 2003; Wu et al., 2008). Consequently, future research should

prioritize understanding the dynamic interplay between climate change and background O₃ concentrations to improve predictive models and inform effective air quality management strategies.

Author contributions

CC collected the data. CC conducted the data analysis and prepared the draft with the support of WC, LG and YW. XD, XW, and MS contributed to the revision of the paper.

Competing interests

The authors declare that they have no conflict of interest.

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