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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 (O_3) refers to O_3 concentrations that remain unaffected by direct local anthropogenic emissions, critical for comprehending tropospheric O_3 pollution, as it defines the baseline levels without local anthropogenic emissions. Accurately estimating background O_3 is essential for determining the maximum achievable reductions in O_3 through anthropogenic precursor emissions control and for developing effective air quality management strategies. This review synthesizes the definition and estimation methods for background O_3, including in situ measurement, statistical analysis, numerical modeling, and integrated method. A meta-analysis of the spatiotemporal distribution of background O_3 across China from 1994 to 2020 reveals substantial spatial variability, with the highest concentrations in the Northwest region (48 ppb) and the lowest in the Northeast and Central regions (~33 ppb). The national average background O_3 concentration is approximately 40 ppb, contributing 77 % to the tropospheric maximum daily 8-hour average ozone. Estimation methods show notable discrepancies: in situ measurement and statistical analysis methods yield higher estimates, while integrated method provide lower yet more consistent values. On a global scale, background O_3 concentrations in China are ranked medium-to-high and exhibit an increasing trend. This review, from a global perspective, highlights the need for integrated estimation methods to improve accuracy, underscores the importance of international collaboration in addressing long-range pollutant transport, and calls for further research on the interactions between background O_3 and climate change. By advancing the understanding of background O_3 dynamics, this study provides critical insights for atmospheric chemistry research and air pollution control efforts in China and beyond.

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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 made significant progress in air quality management, particularly in reducing fine particulate matter ($PM_{2.5}$) concentrations. These policies have been effective in curbing $PM_{2.5}$ levels, with nationwide $PM_{2.5}$ concentrations declining by approximately 50 % from 2013 to 2020 (Geng et al., 2024). However, despite these successes in controlling $PM_{2.5}$, the annual average concentration of ozone (O_3) in major urban clusters has exhibited a persistent upward trend. From 2015 to 2022, the frequency of O_3 pollution days has steadily increased, with urban areas such as Beijing, Shanghai, and Guangzhou experiencing a marked rise in O_3 concentrations (Li et al., 2019; Wang et al., 2023). Notably, large-scale, prolonged O_3 pollution episodes have also become more frequent, with the number of days exceeding the national O_3 standard more than doubling in some regions over the past decade (Ozone Pollution Control Committee of Chinese Society of Environmental Sciences, 2024). Therefore, the "Opinions on Deepening the Fight Against Pollution", issued by the Central Committee of the Communist Party of China and the State Council, acknowledged these challenges and explicitly mandated that the coordinated control of both $PM_{2.5}$ and O_3 should be incorporated into the "14th Five-Year Plan" (2021-2025), signaling a new phase in addressing multi-pollutant control.

O_3 is a secondary pollutant formed through complex photochemical reactions involving volatile organic compounds (VOCs) and nitrogen oxides (NO_x). Tropospheric O_3 refers to O_3 in the lower part of the atmosphere and consists of two primary components: O_3 produced from anthropogenic precursor emissions and background O_3, both of which directly impacts human health, ecological ecosystems, and agricultural productivity (McDonald-Buller et al., 2011; Wang et al., 2009b). Background O_3 refers to the portion of O_3 concentrations that remain unaffected by direct local anthropogenic emissions. Its sources are diverse, including natural emissions from vegetation, soil, lightning, and wildfires, as well as O_3 produced from methane (CH_4) oxidation, stratosphere-troposphere exchange (STE), and the long-range transport of pollutants, as shown in Fig. 1 (Dolwick et al., 2015; Thompson, 2019). It is important to note that in the pre-industrial era (~1750), CH_4 emissions were overwhelmingly dominated by natural

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sources (e.g., wetlands, inland freshwaters, and geological), accounting for approximately 95% of global emissions (Lassey et al., 2000; Prather et al., 2012; Valdes et al., 2005), which contributed to relatively stable atmospheric CH_4 concentrations (Ehhalt et al., 2001; Wuebbles and Hayhoe, 2002). Owing to its long atmospheric lifetime (8-9 years) and well-mixed global distribution, CH_4 played a crucial role in sustaining background O_3 levels on a global scale (Fiore et al., 2002; Vingarzan, 2004; West and Fiore, 2005; Thompson, 2019). Accordingly, CH_4 oxidation has traditionally been regarded as a contributor to background O_3 (Skipper et al., 2021; Sun et al., 2024; Thompson, 2019; Vingarzan, 2004; Wu et al., 2008). However, with the intensification of anthropogenic activities, the proportion of CH_4 emissions attributable to human sources (e.g., agriculture, fossil fuels, landfills and waste) has risen markedly from 31% in 1850 to 61 % by 2012 (Fiore et al., 2002; Jackson et al., 2024; Kirschke et al., 2013; Lelieveld et al., 1998; Saunois et al., 2016). In light of this shift, the contribution of anthropogenically derived CH_4 to O_3 formation can no longer be classified as part of the background component. To improve the accuracy of background O_3 assessments, it is therefore essential that future studies explicitly differentiate and exclude the influence of anthropogenic CH_4 emissions.

Background O_3, primarily influenced by natural sources and large-scale environmental factors (e.g., long-range transport of pollutants, and regional meteorological conditions), typically contributes 60-80 % of total tropospheric O_3 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 controlled through emission reductions, the management of O_3 is more complex and has become a significant challenge in global air quality governance (Chen et al., 2022). Research has shown that reductions in anthropogenic precursor emissions of O_3 have led to declines in pollution episodes in regions such as Europe, the United States, and Japan. However, background O_3 concentrations continue to rise, complicating efforts to reduce overall ground-level O_3 pollution (Akimoto et al., 2015; Cooper et al., 2012; Wilson et al., 2012; Yan et al., 2021). For example, studies from the United States show that while emissions reductions have resulted in fewer O_3 exceedance days, the relative contribution of background O_3 to total ground-level O_3 has risen by approximately 6 % over the past two decades (Jaffe et al., 2018). In recent years, environmental changes such as global climate

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change, increased CH_4 emissions, and transboundary pollution have led to a steady increase in background O_3 levels (Chen et al., 2022; Vingarzan, 2004). This rise is particularly evident in regions like East Asia, where transboundary pollution from neighboring countries exacerbates the problem (Vingarzan, 2004). Furthermore, as emissions of anthropogenic precursors continue to be controlled, it is projected that the relative contribution of background O_3 to overall O_3 pollution will become increasingly significant (Jaffe et al., 2018; Lam and Cheung, 2022; Skipper et al., 2021). This shift will require a rethinking of air quality management strategies, with greater emphasis on mitigating the factors influencing background O_3 levels, such as reducing global CH_4 emissions and addressing transboundary pollution.

Unlike O_3 formed from anthropogenic precursors, background O_3 cannot be mitigated through local emission reductions. Instead, it represents the "baseline" level for regional O_3 pollution, determining the maximum achievable reduction in ground-level O_3 through local anthropogenic emission controls (Fiore et al., 2014; Wang et al., 2009a; Zhang et al., 2011). The increasing levels of background O_3 are complicating air quality management because they limit the effectiveness of local emission reductions (Thompson, 2019; Vingarzan, 2004). In regions such as the United States and Europe, elevated levels of background O_3 undermine the effectiveness of ongoing efforts to meet current O_3 standards and present a major obstacle to meeting more stringent future standards (Thompson, 2019; Vingarzan, 2004). The persistence of high background O_3 levels has become a critical area of scientific and policy research worldwide. For example, the National Aeronautics and Space Administration (NASA) has highlighted background O_3 as a priority issue in efforts to reduce O_3 pollution in the United States (Huang et al., 2015). Similarly, the "*China Blue Book on Prevention and Control of Atmospheric Ozone Pollution (2020)* " recognizes urban O_3 pollution and regional background O_3 concentrations as significant challenges for future O_3 management and emphasizes the need for advanced research to better understand regional variations in background O_3 concentrations and their impact on local air quality (Ozone Pollution Control Committee of Chinese Society of Environmental Sciences, 2022).

The complexity and global implications of background O_3 make it an essential focus of research in atmospheric chemistry, climate change, and air quality management. Its contribution to total tropospheric

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O_3 concentrations is both substantial and difficult to control, as it is influenced by a range of natural and anthropogenic factors beyond the immediate control of local emission regulations. Despite its growing importance, key gaps remain in understanding the sources, variability, and impacts of background O_3. This study aims to provide a comprehensive review of the definitions and estimation methods for background O_3, offering a foundation for advancing scientific understanding in this area. By utilizing publicly available datasets, we systematically examine the spatial and temporal variations of background O_3 across China, uncovering regional heterogeneities, discrepancies between different estimation methods, and key influencing factors. Additionally, we conduct a comparative analysis of China's background O_3 levels with those in other global regions, providing a broader context for understanding the dynamics of background O_3 in the face of global environmental change. This comparative analysis not only reveals the distinct challenges China faces in managing O_3 pollution but also provides broader insights into regional difference in background O_3, reinforcing the importance of the global outlook in addressing this issue. Finally, we propose potential directions for future research on background O_3, emphasizing the importance of filling existing knowledge gaps in this field. As background O_3 continues to influence the effectiveness of O_3 mitigation efforts, this research is pivotal for shaping future air quality management strategies and ensuring the protection of public health and ecosystems.

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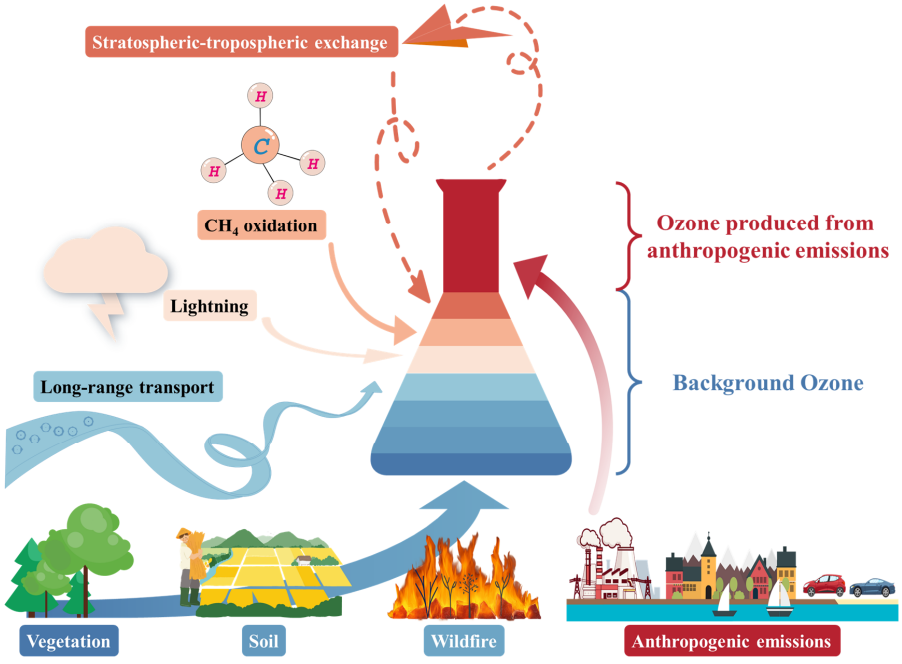

Figure 1: Conceptual diagram of O_3 components and sources.

2 Materials and methods

2.1 Data source and study area

To provide a comprehensive synthesis of advancements in the study of background O_3, 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/O_3, regional background ozone/O_3, and policy relevant background ozone/O_3, ensuring the inclusion of a wide range of relevant studies. This study identified 171 pertinent documents, comprising 134 peer-reviewed English-language papers, 25 peer-reviewed Chinese-language papers, 4 English-language reports, 4 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 O_3 over a span of seven

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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 O_3, we also analyzed the spatial and temporal characteristics of regional background O_3 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 O_3 concentration from various regions and time periods within China. The dataset includes diverse temporal resolutions, such as annual data (31 %, 237 data points), seasonal data (26 %, 195 data points), and monthly data (43 %, 326 data points). To offer a deeper understanding of the seasonal distribution of data, the seasonal and monthly data were further categorized as follows: spring (24 %, 127 data points), summer (28 %, 145 data points), autumn (24 %, 125 data points), and winter (24 %, 124 data points). The seasonal divisions were based on standard meteorological periods: spring (March-May), summer (June-August), autumn (September-November), and winter (December-February). Detailed information on the collected data, including a breakdown of regional and temporal distributions, is provided in Table S1.

To assess the regional differences in background O_3 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 O_3 concentrations presented in this study are expressed as molar mixing ratios in parts per billion (ppb). In some literature, the background O_3 concentrations are reported in micrograms per cubic meter ($\mu g\ m^{-3}$). To ensure consistency with international standard units and facilitate comparisons with global datasets, unit conversion was performed using the following Eq. (1):

$$ppb = \left(\frac{22.4\ L\ mol^{-1}}{48\ g\ mol^{-1}}\right) \times (\mu g\ m^{-3}), \quad (1)$$

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Where 22.4 $L\ mol^{-1}$ represents the molar volume of an ideal gas at standard temperature (0 °C) and pressure (101.325 kPa), while 48 $g\ mol^{-1}$ is the molar mass of O_3.

2.3 Trend analysis

This study employed linear regression analysis to examine the annual trend in background O_3 concentration and assess the statistical significance of these trends over time. Specifically, linear regression was applied to a scatter plot of background O_3 concentrations across different years, using the least squares to determine the relationship between background O_3 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 O_3 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 O_3 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 O_3 concentration, only annual data from our compiled data set were used. Data points from individual studies that significantly deviated from the overall trend were excluded to ensure the robustness of the analysis. However, consecutive data points with large deviations were retained for consistency. Furthermore, when background O_3 concentrations were derived using different methods in the same geographical region within the same study, the results were averaged to provide a more representative value.

3 Background ozone: conceptual evolution and key definitions

Background O_3 generally refers to the portion of O_3 concentrations that are not influenced by direct local anthropogenic emissions, though its definition varies across studies globally. In contemporary atmospheric research, background O_3 is commonly categorized into two distinct types: natural background ozone (NBO) and regional background ozone (RBO). These two categories are crucial for

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understanding the sources and variations of background O_3 on both local and global scales. Figure 2 presents the evolution of background O_3 definitions.

Natural background ozone (NBO) refers to O_3 that forms exclusively through natural processes, independent of anthropogenic emissions (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 CH_4, as well as O_3 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 O_3 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 O_3 concentrations in remote regions, far from urban pollution, suggesting natural processes contributed to O_3 production (Galbally et al., 1986; Volz and Kley, 1988). By the late 1970s, systematic studies in the United States identified key natural sources of O_3, 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 O_3 production (Berlin et al., 2013). Nonetheless, NBO is a critical reference for establishing baseline O_3 levels globally, facilitating the evaluation of human contribution to atmospheric O_3 concentration.

In the 1990s, researchers in the United States began to recognize the critical role of long-range transport from anthropogenic sources in regional O_3 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 O_3 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 O_3 levels could not be fully mitigated through domestic emission reductions alone.

By the early 21st century, research on background O_3 increasingly intersected with air quality policy

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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 O_3 concentrations that exclude all anthropogenic emissions from North America (the United States, 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 O_3 pollution and inform the establishment of stricter O_3 standards. By differentiating controllable from uncontrollable O_3 sources, PRBO enabled a more targeted approach to air quality management, framing policy discussions around the limitations of local pollution control in addressing O_3 levels (Duc et al., 2013; Zhang et al., 2011). The introduction of PRBO marked a significant transition in background O_3 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 United States O_3 concentration. To address regional variations and better capture the dynamic of background O_3 in specific areas, advancements in atmospheric chemistry models have enabled scientists to differentiate the contributions of various sources to background O_3. 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 O_3 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 CH_4, stratospheric-tropospheric exchange, and long-range transport (McDonald-Buller et al., 2011; Skipper et al., 2021; Sun et al., 2024; Wang et al., 2022).

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

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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.

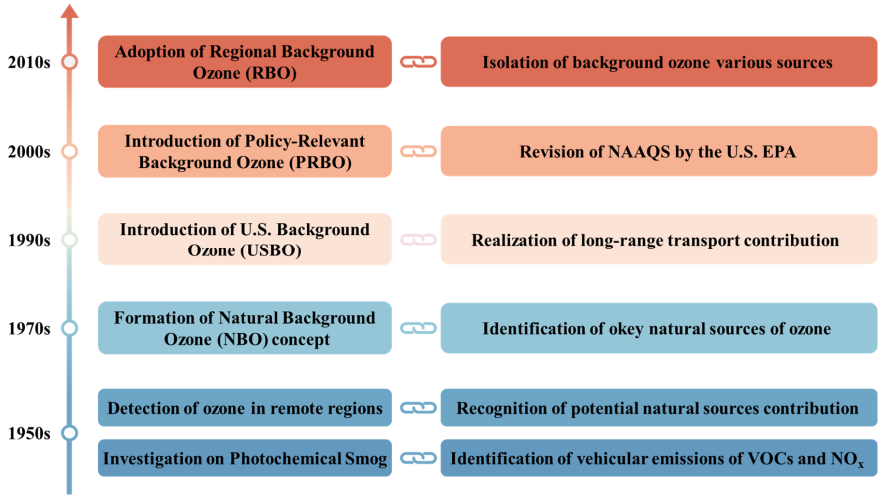

Figure 2: The evolution of background O_3 definitions.

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 method 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 O_3 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 O_3. It is relatively straightforward

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to implement, requires minimal post-measurement processing, and provides continuous, high frequency data on O_3 variations across spatial and temporal scales. These attributes render it an invaluable tool for tracking long-term trends in background O_3 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 O_3 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 O_3 concentrations. For instance, Vingarzan (2004) reported that background O_3 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 O_3 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 O_3 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 O_3 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 O_3 concentration data and applies statistical techniques to estimate regional background O_3 levels (Altshuller and Lefohn, 1996; Berlin et al., 2013; Steiner et al., 2010; Wang et al., 2022). Historically, such estimations primarily relied on real-time

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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 O_3 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 O_3 concentration (Wang et al., 2022). To overcome these challenges, researchers have increasingly adopted advanced statistical models that incorporate diverse observational data sources, enhancing the accuracy and reliability of background O_3 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 O_3 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 O_3 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 O_3 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 O_3 levels, particularly in cases where direct measurements

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are confounded by local pollution or short-term meteorological variability.

Despite its effectiveness, the application of PCA requires substantial computational resources, particularly when processing large datasets with high temporal and spatial resolution. Additionally, the accuracy of PCA results is highly contingent upon the availability of high-quality, long-term observational data. As emphasized by Wang et al. (2022), insufficiently robust datasets can hinder PCA's ability to isolate the true background O_3 signal, resulting in biased or unreliable estimates.

Langford et al. (2009) applied PCA to analyze regional background O_3 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 O_3 data, strongly indicating its relevance as a proxy for background O_3 levels. The estimated background O_3 concentrations at monitoring stations across Texas ranged from 15 to 75 ppb, with higher values typically observed in rural areas with minimal local pollution. Similarly, Suciu et al. (2017) and Berlin et al. (2013) employed PCA to estimate background O_3 levels in Houston, Texas, reporting concentrations between 29 and 50 ppb. In China, Liang et al. (2018) and Wang et al. (2022) applied PCA to estimate background O_3 concentrations, which ranged from 35 to 70 ppb in the Yangtze River Delta region in May 2016 and from 30 to 75 ppb in Shandong Province between 2018 and 2020. These findings underscore the robustness of PCA in estimating background O_3 levels and highlight its versatility across diverse geographical regions, including both developed and developing regions worldwide.

4.2.2 K-means clustering

K-means clustering is an unsupervised, iterative machine-learning algorithm widely employed for grouping data, such as O_3 concentrations, meteorological parameters, and other environmental factors, based on shared characteristics (Riley et al., 2023). Its primary strength lies in the ability to discern patterns within large and complex datasets by clustering observations with similar attributes. Clusters with minimal anthropogenic influence are often interpreted as representative of background O_3 concentrations. These clusters, typically defined by low pollutant levels or specific meteorological conditions, facilitate the identification of periods or locations where regional background O_3 can be reliably assessed (Riley et al., 2023; Zohdirad et al., 2022).

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The computational efficiency of K-means clustering makes it particularly suitable for large-scale studies, as it can simultaneously analyze multiple variables influencing O_3 variability, such as temperature, humidity, and wind patterns. This capability to manage multivariate data enables K-means to derive meaningful insights from complex datasets, which is especially useful in evaluating background O_3 in regions with diverse environmental conditions. For example, Riley et al. (2023) applied K-means clustering to estimate background O_3 concentrations in eastern Australia from 2017 to 2022. Their analysis revealed an average background O_3 concentration of 28.5 ppb, with a decadal increase of 1.8 ppb, reflecting the global trend of rising background O_3 levels.

Despite its utility, the effectiveness of K-means clustering is highly dependent on the quality of input data. The algorithm is sensitive to noise, outliers, and inconsistencies, which can undermine the reliability of its results. For example, extreme weather events or episodic pollution spikes can distort the clustering process, leading to inaccurate estimations of background O_3. Consequently, high-quality, well-preprocessed datasets are essential to ensure robust and reliable outcomes. Furthermore, K-means clustering is a descriptive rather than a causa technique, meaning it identifies associations between variables but does not elucidate the underlying physical or chemical mechanisms of O_3 formation (Govender and Sivakumar, 2020; Ning et al., 2024; Riley et al., 2023). To mitigate these limitations and enhance the accuracy of background O_3 estimates, K-means clustering can be integrated with other complementary analytical methods, combining its descriptive power with approaches that provide deeper causal understanding (Riley et al., 2023).

4.2.3 TCEQ method

The Texas Commission on Environmental Quality (TCEQ) method, based on O_3 monitoring data from background regions, has been widely adopted in Texas, the United States, as a reliable approach for estimating regional background O_3 levels (Nielsen-Gammon et al., 2005). This approach defines regional background O_3 as the minimum value within the maximum daily 8-hour average (MDA8) O_3 across all monitoring stations in a given area, effectively representing the lowest O_3 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

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evaluating long-term trends in O_3 pollution.

Compared to more complex statistical methods such as PCA, the TCEQ method is simpler to implement and often yields more consistent and interpretable results. However, it is not without limitations. The method is sensitive to meteorological variability, which can lead to temporary spikes or drops in O_3 concentrations, potentially affecting accuracy. Additionally, the TCEQ method requires a dense network of monitoring stations to accurately represent regional background O_3 levels, as sparse monitoring coverage may fail to capture true background concentrations (Wang et al., 2022; Wu et al., 2017).

Despite these limitations, the TCEQ method has provided valuable insights into background O_3 levels across various regions. For instance, Berlin et al. (2013) and Langford et al. (2009) used this method to estimate background O_3 concentrations during high-O_3 periods (May-October) in Texas between 2000 and 2012. Their estimates ranged from 25 to 45 ppb and 40 to 80 ppb, respectively. Beyond the United States, the TCEQ method has been applied in diverse geographical regions, further underscoring its utility. For example, Xue et al. (2014) applied the TCEQ method to estimate background O_x (O_3 + NO_2) concentrations in Hong Kong from 2002 to 2013, reporting an average O_x concentration of 54 ppb with an annual increase of 0.52 ± 0.55 ppb yr^{-1}, highlighting the growing trend of background O_3 pollution in urbanized regions of Asia. Similarly, Wang et al. (2022) estimated background O_3 concentrations in Shandong Province, China, to average 31.4 ppb from 2018 to 2020. These findings demonstrate that the TCEQ method is adaptable across different geographical contexts and provides robust background O_3 estimates that can inform air quality management strategies and policymaking.

4.2.4 O_3-NO_z 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

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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.

One of the key strengths of this method lies in its simplicity, as it requires only reliable measurements of O_3, NO_x, and NO_y without necessitating extensive observational networks. However, the method's validity depends heavily on the assumption of a linear relationship between O_3 and NO_z, which may not hold under all atmospheric conditions. For instance, photochemical processes, such as the formation of secondary pollutants, meteorological variability (e.g., wind, temperature), and local environmental factors can introduce non-linearities into the O_3-NO_z relationship, potentially impacting the accuracy of the estimates. Additionally, the method's precision is highly sensitive to the quality of O_3, NO_x, and NO_y measurements, as inaccuracies in these data can result in significant biases when estimating background O_3 levels.

Several studies have applied the O_3-NO_z intercept method to estimate background O_3 concentrations in various regions, providing valuable insights into its efficacy and limitations. For example, Hirsch et al. (1996) applied this method at Harvard Forest in the United States, estimating background O_3 concentrations of 40 ppb in May and 25 ppb in September. Similarly, Yan et al. (2021) applied the method in the southeastern United States during the summer of 2013, estimating background O_3 concentrations of 29.8 ppb in a region influenced by both local emissions and regional transport of pollutants. 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-σ 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. The modified method estimated background O_3 concentration at 21.3 ppb, approximately 8 ppb lower than the traditional O_3-NO_z method, demonstrating enhanced reliability under conditions with

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elevated nitrogen deposition. This modification highlights the importance of accounting for nitrogen deposition dynamics to improve the robustness of background O_3 estimations.

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 across a broad range of conditions. 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.

In model-based applications, tracer simulations provide the necessary inputs to determine the unknown variables on the right-hand side of Eq. (3), facilitating the estimation of background O_3 concentrations. This capability makes the method particularly valuable in model-based studies, where emissions sources and their contributions are explicitly tracked. Conversely, when applied to observational data, distinguishing the origins of various species presents challenges. Empirical methods can be employed to approximate missing variables, combining observational data with nonlinear regression analysis, as described in Eq. (2). This enables the estimation of background O_3 concentrations

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even in the absence of precise source-specific information.

However, it is important to note that the chemical interactions among O_3, CO, and HCHO are inherently nonlinear and influenced by regional geography, meteorological conditions, and other environmental factors. These complexities may limit the method's accuracy, as its performance is highly context dependent. (Cheng et al., 2018; Yan et al., 2021). Specifically, the current methodology is most effective in regions minimally affected by anthropogenic pollution, where HCHO is primarily formed via the oxidation of biogenic isoprene, such as in the southeastern United States. A limitation of this method is the difficulty of disentangling contributions from natural and anthropogenic O_3 precursors. Nevertheless, Yan et al. (2021) proposed integrating the O_3-CO-HCHO method with an "anthropogenic-source-zeroing" scenario, which can estimate the impact of emissions from natural sources.

Applying the O_3-CO-HCHO method, Yan et al. (2021) estimated the background O_3 concentration in the inland regions of the southeastern United States during the summer of 2013 to range between 10-15 ppb, approximately 5-10 ppb lower than estimates derived from other methods. This refinement highlights the utility of the O_3-CO-HCHO method for achieving more accurate assessments of zero-chemical-signature background O_3 concentrations.

4.2.6 Percentile method

The percentile method is a widely adopted statistical analysis estimation 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.

A key advantage of the percentile method lies in its simplicity and ease of implementation, making it particularly suitable for regions with limited monitoring networks or computational resources required for advanced modeling techniques. However, the reliability and accuracy of this method are highly dependent on the selection of the appropriate percentile value, which can vary significantly depending on regional characteristics such as emissions patterns, meteorological conditions, and topographical

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features (Cooper et al., 2012). Consequently, the chosen percentile may exhibit significant variability across different geographical regions, potentially affecting the consistency of background O_3 estimates. For example, Akimoto et al. (2015) proposed using the 2nd percentile of MDA8 O_3 concentrations as a suitable measure of background O_3 levels in Japan, capturing low concentrations unaffected by local anthropogenic emissions during high-O_3 episodes. In contrast, Yan et al. (2021) applied the 5th percentile to estimate background O_3 concentrations in the southeastern United States. Similarly, Cooper et al. (2012) and Wilson et al. (2012) advocated for the use of the 5th percentile in their studies of background O_3 levels in the United States and Europe, respectively, suggesting it achieves a balance between accurately representing background O_3 levels and accounting for regional variations in pollutant emissions.

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).

This method offers several advantages, primarily its simplicity and reliance on widely available observational meteorological and O_3 concentrations data. Given the accessibility of temperature datasets, the temperature-ozone relationship method is particularly effective for conducting large-scale spatial and temporal analyses. Its versatility is demonstrated by its applicability across diverse geographic regions and climatic conditions, ranging from temperate zones to tropical climates, where temperature plays a key role in driving O_3 dynamics.

Despite its practicality, the method has certain limitations. A primary challenge is the variability in the temperature range corresponding to stable O_3 levels, which differs among regions due to local

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meteorological and geographical factors. Extreme meteorological conditions, such as high humidity or strong winds, can disrupt the temperature-ozone correlation, reducing the reliability of this method in such scenarios. Moreover, O_3 formation is influenced by multiple factors, including solar radiation, precursor emissions, and atmospheric chemistry, making temperature an incomplete predictor of O_3 dynamics. The method's accuracy also depends on the quality and temporal resolution of the data used; short-term datasets, such as those based on monthly averages, can introduce significant uncertainties due to O_3's sensitivity to short-term meteorological fluctuations and emission variations. This limitation underscores the importance of using long-term, high-resolution datasets to derive more reliable temperature-ozone relationships (Li et al., 2020; Liao et al., 2021). Incorporating seasonal and regional variations in temperature and O_3 formation processes can further enhance the method's accuracy.

Despite these challenges, the temperature-ozone relationship method has been successfully applied in several studies to estimate background O_3 concentrations. For example, Steiner et al. (2010) applied this method to estimate the average background O_3 concentrations in California during the summer months (June-October) between 1980 and 2005, finding values ranging from 30 to 40 ppb. Similarly, Chen et al. (2022) used this method to assess background O_3 levels in China from 2013 to 2019, reporting concentrations of 35-40 ppb during clean seasons and 50-55 ppb during O_3-polluted seasons.

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 O_3 levels (Chan et al., 2003). At night, O_3 levels generally remain constant or exhibit minimal fluctuations, as they are primarily governed by the equilibrium between O_3 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 O_3 and NO, which produces NO_2 and depletes ambient O_3 levels. This phenomenon, known as O_3 titration, can result in underestimation of true background O_3 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 O_3 titration, researchers have introduced adjustments to nocturnal O_3

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estimates by incorporating a "total O_3" concentration, denoted as $O_{3_{total}}$, which serves as a proxy for background O_3 levels. The "total O_3" is calculated using the following equations:

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

Here, $[O_3]$, $[NO_2]$, and $[NO_x](= [NO] + [NO_2])$ represent the mixing ratios of O_3, NO_2, and NO_x, respectively. The parameter α accounts for the fraction of NO_2 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 $[O_{3_{total}}]$. This adjustment helps to compensate for the effects of NO titration, yielding a more accurate representation of regional background O_3 levels.

Despite its utility, the nocturnal O_3 concentration method is subject to inherent limitations. A primary drawback is its reliance on observational data, which can be influenced by local variations in emissions and meteorological conditions, thereby complicating the estimation process.

In an applied context, Chen et al. (2022) used the nocturnal O_3 concentration method to estimate background O_3 levels across China during the period from 2013 to 2019. Their analysis revealed that background O_3 concentrations ranged between 25 and 38 ppb during clean seasons and between 35 and 49 ppb during O_3-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 O_3 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 O_3 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,

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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 O_3 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 O_3 concentrations (Dolwick et al., 2015; Guo et al., 2018; Hogrefe et al., 2018; Jaffe et al., 2018).

Numerical models typically estimate regional background O_3 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 O_3 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 O_3 levels (Zhang et al., 2011; Li et al., 2018; Lu et al., 2019; 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 O_3 concentrations. Models such as CMAQ-ISAM and CAMx-OSAT, developed by the United States Environmental Protection Agency (EPA), incorporate tracer methods to estimate regional background O_3 concentrations (Lefohn et al., 2014; Li et al., 2012; Reid et al., 2008).

Although both methods have their strengths, studies have highlighted discrepancies in O_3 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 O_3 concentrations in the United States compared to GEOS-Chem, with CAMx showing a higher correlation with observational data, especially at remote stations and during high-O_3 episodes. Conversely, GEOS-Chem demonstrated

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greater accuracy in capturing seasonal mean O_3 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 O_3 concentrations in suburban United States areas across both methods. However, in urban areas, the tracer method yielded lower background O_3 estimates than the emission scenario method, indicating a substantial influence of local emissions on O_3 concentrations in densely populated regions. Equally, Fiore et al. (2014) reported differences in background O_3 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 O_3 concentrations. For example, using the global model GEOS-Chem, Emery et al. (2012) and Zhang et al. (2011) estimated average background O_3 concentration in the United States 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 O_3 concentration in the United States between June and August from 2004 to 2012. Meanwhile, regional models such as CAMx and CMAQ yielded background O_3 estimates of 25 to 50 ppb in the United States between March and August 2006 (Emery et al., 2012). In China, Sahu et al. (2021) found background O_3 concentrations exceeded 22 ppb in 2015.

4.4 Integrated method estimation

The three methods discussed above each possess distinct advantages and limitations, contributing to uncertainties in estimating regional background O_3 concentration. Given these challenges, researchers have increasingly turned to integrated method estimation methods to improve the accuracy and reliability of these estimations.

For instance, Dolwick et al. (2015) improved model-based estimates of background O_3 by comparing observed and simulated O_3 concentrations. Their analysis of rural areas in the western United States during April to October 2007 reported background O_3 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,

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optimizing regional background O_3 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 O_3 and anthropogenic emissions. This revised approach estimated an average background O_3 concentration of approximately 33 ppb for the United States 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 method 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 O_3 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 O_3 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 O_3 concentrations in 13 urban areas of the United States during April-June and July-September 2016 to range from 31-46 ppb and 27-45 ppb, respectively. This finding underscore the potential of ML algorithms to enhance model-based background O_3 estimates by capturing nonlinear relationships and complex variable interactions (Breiman, 2001; Kashinath et al., 2021).

Overall, integrated method estimation methods, particularly those integrated with machine learning techniques, represent a significant advancement in estimating regional background O_3 concentrations. These approaches not only improve the accuracy and robustness of estimates but also provide valuable insights into the complex dynamics of O_3 formation and transport. By combining observational data, statistical adjustments, and advanced modeling techniques, researchers can achieve a more comprehensive understanding of regional O_3 levels and their temporal variations.

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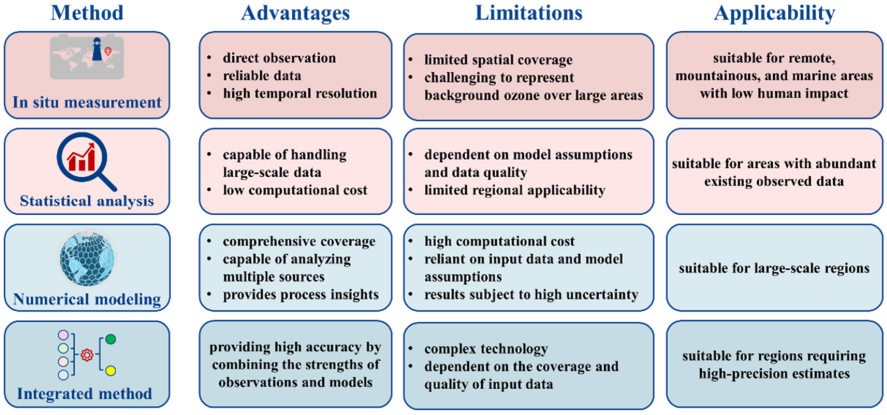

Figure 3: Summary of the advantages, limitations, and applicability of different estimation methods for background O_3.

5 Comprehensive assessment 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 O_3 concentrations across China and its various regions. On a national scale, the average background O_3 concentration is 40.3 ± 11.9 ppb, accounting for 77 % of the MDA8 O_3 concentration. Notable regional variability in background O_3 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 O_3 concentrations, reaching 48.2 ± 8.3 ppb, which accounts for 96 % of the MDA8 O_3 concentration. This elevated concentration is attributed to several interrelated factors. First, strong solar radiation and arid atmospheric conditions enhance photochemical reactions, accelerating O_3 formation. He et al. (2021) demonstrated that abundant sunshine and dry conditions significantly increase O_3 production due to the intensified photolysis of precursor compounds. Furthermore, the high altitude and unique surface characteristics of Northwest China promote strong daytime atmospheric convection, facilitating the downward transport of O_3 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

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result in fewer precursors like NO_x and VOCs, thereby minimizing rapid fluctuations in O_3 levels. The weaker nocturnal O_3 depletion, caused by limited O_3 scavenging from sparse emissions and lower nighttime temperatures, further amplifies baseline O_3 concentrations (Nie et al., 2004; Qin et al., 2023; Xu et al., 2020).

Southwest China (SWC), alongside with the urban clusters of East China (EC) and North China (NC), also exhibits higher background O_3 concentrations, averaging 38.7 ± 10.8 ppb, 38.4 ± 13.0 ppb, and 37.7 ± 13.5 ppb, respectively. These concentrations account for 84 %, 66 %, and 71 % of the MDA8 O_3 concentration in each respective region. In Southwest China, regional pollutant transport plays a significant role. During the spring, prevailing winds carry pollutants such as NO_x and VOCs from Southeast Asia, intensifying local O_3 levels (Ye et al., 2024). Summer conditions - characterized by high humidity, elevated temperatures, and intense solar radiation - further amplify photochemical O_3 formation (Chen, 2020). The region's complex topography, including mountainous areas and plateaus, also contributes to localized O_3 accumulation. For instance, the Sichuan Basin, with its basin - like terrain, impedes air mass dispersion, leading to pollutants entrapment and prolonged O_3 buildup (Hu et al., 2019). In contrast, East China and North China 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 O_3 levels. Moreover, the East Asian Summer Monsoon (EASM) facilitates the transport of O_3 and its precursors from low-latitude regions, such as South China, to higher latitudes, exacerbating O_3 pollution during the monsoon season (Gao et al., 2005; Liu et al., 2019, 2021; Sun et al., 2016; Xu et al., 2011, 2020)

The background O_3 concentrations in South China (SC), Central China (CC), and Northeast China (NEC) are relatively low compared to other regions of China, with values of 35.5 ± 8.0 ppb, 33.2 ± 10.9 ppb, and 33.0 ± 5.7 ppb, respectively. These concentrations account for 71 %, 57 %, and 67 % of the MDA8 O_3 in each corresponding region. In South China, the relatively low background O_3 concentrations can be primarily attributed to the frequent rainfall and high humidity, which facilitate the removal of O_3 precursors such as NO_x and VOCs, thereby suppressing O_3 formation (He et al., 2021). Although BVOCs emissions are relatively high in this region due to abundant vegetation and elevated

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temperatures, their impact on O_3 formation is less pronounced compared to regions like North China. This is because anthropogenic emissions, such as vehicular exhaust and industrial discharges, typically amplify the contribution of BVOCs on O_3 formation. In the absence of significant anthropogenic pollution, the role of BVOCs in O_3 formation remains relatively limited (Ye et al., 2024). Moreover, the mixed topography of South China, characterized by a combination of hilly terrain and plains, promotes air mixing and disperse O_3, preventing its prolonged accumulation at the surface (Wang et al., 2011).

In Central China (CC), the lower background O_3 concentrations are linked to the region's inland locations, which reduces its exposure to oceanic influences and transboundary pollutant transport. The absence of strong maritime airflow limits the import of O_3 precursors, while frequent rainfall during the warmer months helps remove these precursors from the atmosphere, further suppressing O_3 formation (Sahu et al., 2021). Anthropogenic emissions, primarily from vehicular exhaust, industrial discharges, and solvent usage, constitute the dominant sources of O_3 in this region (Zeng et al., 2018). Consequently, the relative contribution of background O_3 is lower, as anthropogenic emissions play a more substantial role in O_3 formation. The combination of moderate meteorological conditions and limited transport of O_3 precursors contributes to the observed lower background O_3 levels in Central China. In Northeast China, the lower background O_3 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 O_3 generation (Chen, 2024; Xu et al., 2020).

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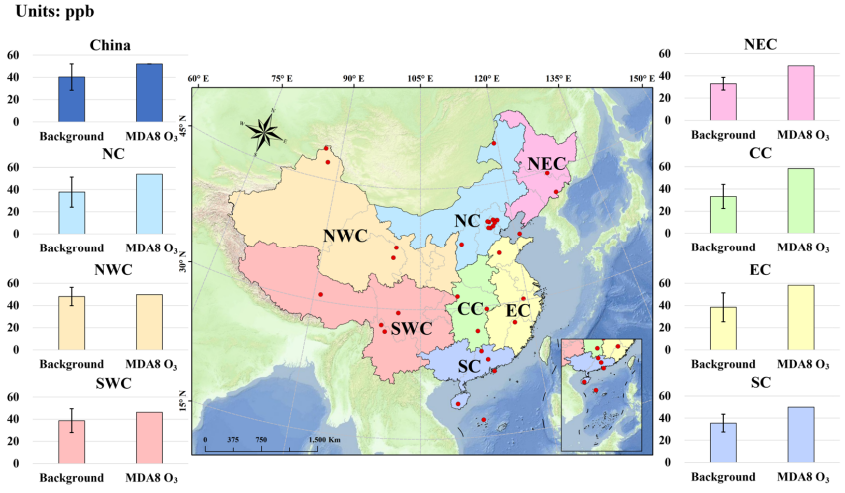

Figure 4: Spatial distribution of background O_3 concentrations (1994-2020) and MDA8 O_3 concentrations across various regions of China. MDA8 O_3 concentrations for the seven regions (2013 to 2018) were sourced from He et al. (2023). The locations of 33 background monitoring stations are indicated with 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 comparison of average background O_3 concentrations across China, as estimated using various methods. Among these, the in situ measurement estimation method remains the most widely utilized, as it directly relies on observational data from established monitoring networks. In this study, data from 33 background monitoring stations were compiled (Fig. 4), with detailed information on their locations and characteristics provided in Table S3. In contrast, the other three methods, particularly the integrated method estimation approach, have been less frequently applied in research, reflecting their higher reliance on assumptions and advanced modeling techniques.

The estimated background O_3 concentrations for China derived from the four methods reveal relatively small differences in average values. The in situ measurement estimation method and statistical analysis estimation method yield the highest average concentration, with values of 40.6 ± 12.0 ppb and 39.9 ± 11.5 ppb, respectively, followed by the numerical modeling estimation method (36.5 ± 12.6 ppb). The integrated method estimation method, which integrates observational data with modeling outputs,

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723 reports the lowest estimate (34.0 ± 2.7 ppb), approximately 6 ppb lower than those from in situ
724 measurement estimation and statistical analysis estimation methods.

725 Despite the similar average values, substantial discrepancies exist among the various methods used
726 to estimate background O_3 concentrations, underscoring the significant influence of methodological
727 differences. The in situ measurement estimation reveals a particularly wide variability, with estimated
728 background O_3 concentrations ranging from approximately 14 ppb to as high as 85 ppb. This broad range
729 reflects the substantial influence of localized factors, such as topography, climatic conditions, and
730 anthropogenic emissions, on observational data. In comparison, statistical analysis estimation and
731 numerical modeling estimation methods yield relatively consistent results, although the difference
732 between the maximum and minimum estimated background O_3 concentration for both methods reach 60
733 ppb. Notably, more than 80 % of the estimated background O_3 concentrations fall within the range of 25-
734 53 ppb, suggesting a reasonable degree of agreement between the two methods. The consistency is likely
735 attributable to the reliance on long-term data trends and calibrated algorithms, which effectively reduce
736 the impact of extreme values while capturing broader patterns in O_3 behavior. The integrated method
737 estimation method, by integrating observational data, statistical analysis, and numerical results, exhibits
738 the least variability. Background O_3 estimates from this approach are confined to a narrower range of 28-
739 39 ppb, reflecting its ability to reconcile the inherent variability in observational data with the structured
740 consistency of numerical models. This reduced uncertainty enhances the method's reliability for both
741 scientific research and policy applications.

742 These differences highlight the complexities and challenges associated with estimating background
743 O_3 concentrations using diverse methodologies. The variability observed across methods arises from
744 several key factors, including disparities in data sources, underlying assumptions, and the
745 parameterization of physical and chemical processes (Jaffe et al., 2018; Skipper et al., 2021; Wang et al.,
746 2022; Yan et al., 2021). For instance, the in situ measurement estimation method is directly influenced
747 by local meteorological and emission conditions, while the numerical modeling estimation method is
748 subject to uncertainties in simulating processes such as natural emissions, transboundary transport, and
749 photochemical reactions. Although the integrated method estimation method benefits from leveraging

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both observations and modeled outputs, it may introduce additional uncertainty through integration techniques and sensitivity to the input data quality.

The discrepancies among these methods emphasize the need for further refinement and rigorous cross-validation to improve the accuracy and reliability of background O_3 concentration estimates. Future efforts should prioritize the expansion and enhancement of observational networks, the refinement of model parameterization schemes, and the development of advanced integrated method frameworks. Such advancements are essential for narrowing the discrepancies among different estimation methods, providing consistent and reliable background O_3 estimates, and enabling more effective air quality management and policy formulation.

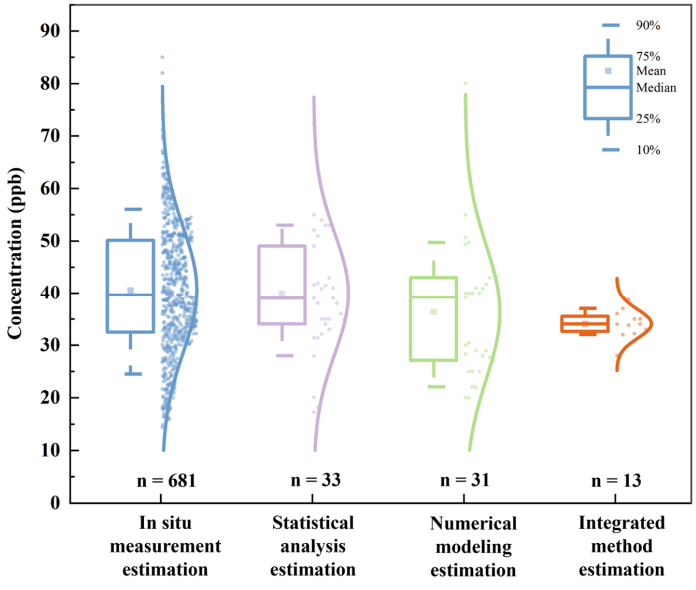

Figure 5: Estimated regional average background O_3 concentrations in China (1994-2020) based on multiple methods.

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

Due to the absence of long-term background O_3 concentration data for other regions, Figure 6 focuses on the annual variation trends of background O_3 concentrations in four major regions of China (i.e., NWC, NC, EC, and SC) during the period from 1994 to 2020. Overall, background O_3 concentrations in these regions have exhibited an upward trend over the years, albeit with notable differences in growth rates

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across regions.

Notably, Northwest China (NWC) exhibited the most pronounced increase in background O_3 concentration, with an average annual growth rate of 0.32 ppb yr^{-1} (r^2=0.68, $p<0.01$), as shown in Fig. 6(a). This marked growth is likely driven by the stratospheric-tropospheric exchange and regional transport of O_3 precursors, as suggested by Xu et al. (2018) and Zhang et al. (2020). Previous studies have highlighted the significant role of long-range transport of air pollutants in this region, contributing to elevated O_3 levels. In addition, shifts in atmospheric circulation and an increase in the frequency of stratospheric-tropospheric exchange events further amplify O_3 concentration in this region (Xu et al., 2016, 2020; Xue et al., 2011).

Following, North China (NC) and East China (EC) also experienced notable increases in background O_3 concentration, each with an average annual growth rate of 0.26 ppb yr^{-1}, as shown in Fig. 6(b) and Fig. 6(c). However, a statistically significant upward trend was observed in North China, where the increase passed the 0.01 confidence level. In contrast, the growth rate in East China, though comparable, did not achieve statistical significance ($p>0.05$), suggesting regional variability in the factors driving O_3 trends. This discrepancy could be attributed to differences in urbanization levels, industrialization intensity, and meteorological conditions, which modulate the dispersion and chemical transformation of O_3 precursors differently in these regions (Ma et al., 2016; Xu et al., 2020; Zhang et al., 2020). A detailed study by Ma et al. (2016) further supports these findings, reporting a higher growth rate in background O_3 concentration in North China, reaching 1 ppb yr^{-1} (r^2=0.58, $p<0.01$), based on data from the Shangdianzi background station. This finding highlights the intensification of regional background O_3 pollution, likely driven by both local emissions and the regional atmospheric conditions conducive to O_3 accumulation.

In stark contrast, South China (SC) experienced the slowest growth in background O_3 concentration, with an average annual increase of only 0.19 ppb yr^{-1} (r^2=0.21, $p<0.05$), as shown in Fig. 6(d). This relatively modest increase may be attributed to a combination of factors, including more stable natural and anthropogenic emission sources and more effective atmospheric cleansing processes (Qin et al., 2021; Shen and Wang, 2012; Xie et al., 2022; Zhang and Zhang, 2019). For instance, the region's comparatively

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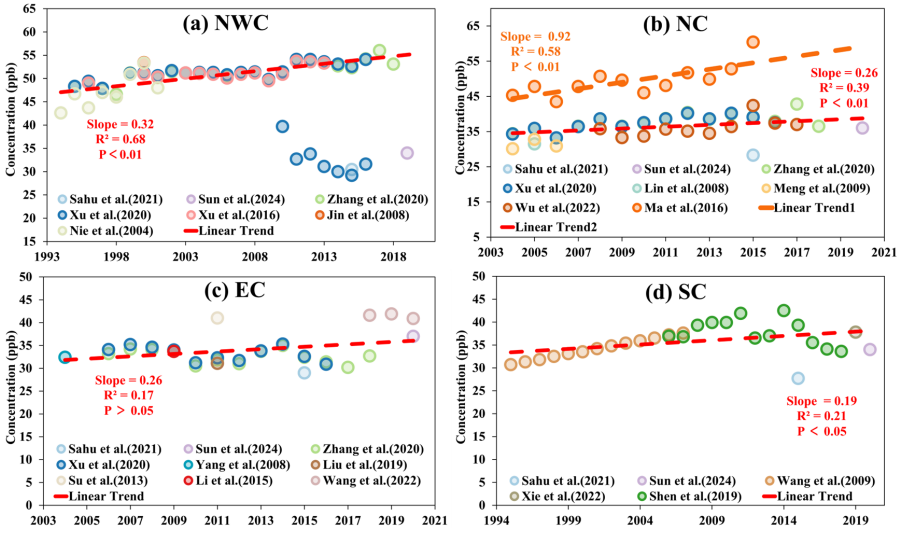
794 higher precipitation rates and frequent weather systems facilitate the removal of pollutants from the
795 atmosphere, thereby moderating O_3 levels.



796

797 **Figure 6: Annual trend of background O_3 concentrations in the NWC (1994-2019), NC (2004-2020), EC (2004-**
798 **2020), and SC regions (1995-2020). The dashed lines represent the linear trends.**

799 **5.4 Source attribution and analysis of background ozone in China**

800 The analysis above reveals that the growth characteristics of background O_3 concentrations across
801 different regions of China are influenced by the synergistic effects of multiple factors, including regional
802 natural source emissions, cross-regional transport, stratospheric-tropospheric exchange, and local
803 atmospheric pollutant reduction measures. These factors interact in complex and dynamic ways, resulting
804 in significant regional and seasonal variations in background O_3 levels.

805 Natural source emissions are a key driver of background O_3 levels in China, with studies
806 consistently highlighting their substantial contribution. For example, Wang et al. (2011) and Lu et al.
807 (2019), using the numerical model GEOS-Chem, estimated that over 70 % of regional background O_3
808 concentrations in China originate from natural emissions, including BVOCs, soil NO_x, and CH_4
809 emissions and others. Among these, BVOCs exert a particularly significant impact on O_3 formation. Lu
810 et al. (2019) demonstrated that during the peak summer months of July and August in 2016-2017, BVOCs
811 emissions contributed over 15 ppb to the background O_3 in central and eastern China. Similarly, Chen et

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al. (2022) emphasized that during O_3 pollution seasons, BVOCs emissions dominate the increase in background O_3, 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 O_3 concentration across China. Several studies have shown that the influx of O_3 and its precursors from other regions, including Southeast Asia, Europe, North America, India, and the Middle East, can elevate background O_3 concentration in China by 2-15 ppb (Wang et al. (2011), Li et al. (2014), and Ni et al. (2018)). This influence is particularly pronounced during specific seasons when atmospheric circulation facilitates the transboundary transport of atmospheric pollutants (Ni et al., 2018; Sahu et al., 2021; Ye et al., 2024). Regional transport also significantly influences the background O_3 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. Similarly, Wang et al. (2009b) measured that air masses from eastern China had an average O_3 concentration of 48 ppb at a background station in Hong Kong, highlighting the significant impact of inter-regional transport on coastal regions.

Stratospheric-tropospheric exchange (STE) is a critical vertical transport process contributing to background O_3 levels, particularly in high-altitude and northern regions of China. This process is most active during spring, when stratospheric O_3 is transported downward into the troposphere (Ding and Wang, 2006; Lu et al., 2019; Xu et al., 2018). Wang et al. (2011) estimated that STE contributes approximately 7 ppb to background O_3 concentrations in northern China during the spring season. 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 O_3 concentrations during spring. Lu et al. (2019) found that STE processes contribute as much as 20 ppb to background O_3 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

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that vertical transport processes, including STE, predominantly influence background O_3 levels during spring and autumn. These findings underscore the critical role of altitude and latitude in modulating the magnitude of STE contributions.

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

Figure 7 presents a comparative analysis of background O_3 concentrations in China and several other global regions, with a particular focus on the United States, Canada, Europe, Japan, and South Korea. On average, background O_3 concentrations in China (40.3 ± 12.0 ppb) are slightly higher than those observed in the United States (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 O_3 precursors, background O_3 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 O_3 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 O_3 formation.

When comparing China to other East Asian regions, the background O_3 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 O_3 levels that are 3-20 ppb higher than those observed in Europe, the United States, 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 O_3 precursors. These

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factors collectively enhance photochemical O_3 (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 O_3, especially in densely populated urban centers. These findings underscore the critical need for regional cooperation in addressing O_3 pollution in East Asia, where transboundary influences and shared atmospheric conditions complicate the management of background O_3 levels.

A more granular regional comparison reveals notable differences in background O_3 concentrations among various regions of both China and the United States. Specifically, the difference in background O_3 concentrations between Central and Western China (including NWC and SWC) reaches 10 ppb, while the discrepancy between the Eastern and Western United States is as high as 13 ppb. Western China and the Western United States exhibit higher background O_3 levels. In particular, the Los Angeles area in the Western United States reports background O_3 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 O_3 formation. Similarly, the higher altitudes of Western China enhance its susceptibility to stratospheric transport, which contributes to elevated O_3 concentrations. The Western United States is similarly influenced by trans-Pacific atmospheric transport, further exacerbating O_3 levels.

In contrast to the significant regional differences observed in China and the United States, background O_3 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 O_3 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 O_3 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 O_3 levels (Miranda et al., 2015; Næss, 2004; Rodrigues et al., 2021; Xu et al., 2019).

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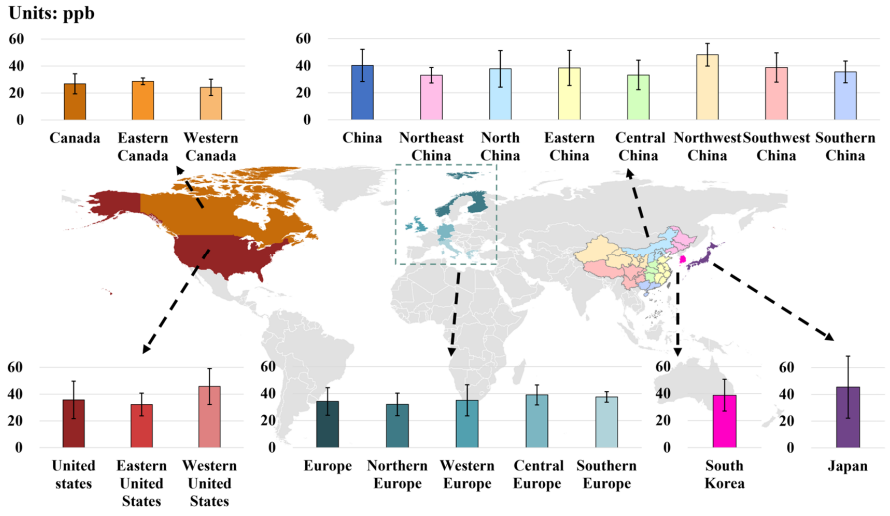

Figure 7: Average background O_3 concentrations in the United States, Canada, Europe, South Korea, Japan, and China.

6 Conclusions and perspectives

Background O_3 concentrations are critical for understanding O_3 pollution, as they represent the baseline level of O_3 even in the absence of local anthropogenic emissions. These concentrations determine the maximum achievable reduction in O_3 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 O_3 concentrations, with a focus on recent advances in regional research in China. Our findings reveal an average background O_3 concentration of 40.3 ± 11.9 ppb in China, which accounts for 77 % of the tropospheric MDA8 O_3. Notable spatial variations are observed, with the highest levels in Northwest China (48.2 ± 8.3 ppb) and the lowest in Northeast China (33.0 ± 5.7 ppb), alongside an upward national trend reflecting growing O_3 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 method estimation method offers lower but more consistent estimates. Compared to other regions, East Asia, including China, South Korea, and Japan, experiences background O_3 levels 3-20 ppb higher than the United States,

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Canada, and Europe. This highlights the region-specific atmospheric conditions and pollution characteristics, and the imperative of addressing background O_3 pollution within a global framework.

Although substantial progress has been made in estimating background O_3 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 O_3:

6.1 Accurate quantification of background ozone sources and processes

Natural emissions, long-range transport, and stratospheric-tropospheric exchange (STE) are key drivers of background O_3 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 O_3, with studies indicating significant seasonal and regional variations in its contribution (Lu et al., 2019; 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 O_3 concentrations is compromised, resulting in increased uncertainties that hinder effective policy planning and air quality management.

6.2 Development of integrated method techniques

Single method approaches for estimating background O_3 concentrations have inherent limitations, as they often fail to capture the full spectrum of factors influencing O_3 levels. For example, while numerical models provide valuable insights, they frequently underestimate actual O_3 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

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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 method techniques presents a promising approach to improve background O_3 estimation. By integrating observational data, statistical analysis, and numerical results, integrated method 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 O_3 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 O_3 estimates, enabling precise characterization of O_3 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 method techniques to provide more accurate and comprehensive background O_3 estimates, future research should prioritize their continued development and validation. Such efforts will improve the precision and reliability of background O_3 estimates, thereby enhancing our understanding of regional O_3 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 O_3 become increasingly stringent, background O_3 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 O_3 levels. For instance, studies conducted in the United States have demonstrated that despite substantial reductions

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in local emissions of O_3 precursors, background O_3 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 O_3 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 O_3.

International collaboration is therefore essential for tackling the elevated background O_3. To this end, fostering transboundary emission reduction agreements between countries and regions can play a pivotal role in curbing the long-range transport of O_3 and its precursors. Moreover, strengthening the global background O_3 monitoring network, particularly in remote regions and marine stations, would significantly enhance the capacity for real-time monitoring of background O_3 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 O_3 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 O_3 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 O_3 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 O_3. Alterations in wind patterns and monsoon systems, for example, could significantly alter the transport of O_3 and its precursors over large distances, thereby exacerbating regional background O_3 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 O_3 concentrations to improve predictive models and inform effective air quality management strategies.

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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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