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Key Points:

- Vegetation growth plays a critical and nonlinear role in future ozone pollution
- The impact of biogenic emissions on ozone depends on anthropogenic emission levels
- Future policies must synergize vegetation expansion with deep emission reduction targets

Supporting Information:

Supporting Information may be found in the online version of this article.

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Impacts of Vegetation-Driven BVOC Emissions on Ozone Pollution in the Beijing-Tianjin-Hebei Region Under a Carbon Neutrality Pathway

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Abstract To achieve air quality improvement and carbon neutrality, China is simultaneously implementing deep anthropogenic emission cuts and promoting large-scale vegetation expansion. However, increased BVOC emissions from growing vegetation may counteract the air quality benefits of emission controls. Using the WRF-Chem model for the Beijing-Tianjin-Hebei region, we find vegetation growth will increase July BVOC emissions by 13.8% in 2040 and 27.4% in 2060 from 2019 levels. Crucially, the impact on O₃ depends on the stage of anthropogenic emission reductions. In 2040, increased BVOCs raise urban MDA8 O₃ by 3.5 ppb, offsetting 47.0% of the benefit from emission controls. However, by 2060, deep emission reductions induce a transition to a NO_x-limited regime; consequently, the O₃ penalty from BVOCs drops to 1.0 ppb (offsetting 7.0%). Our findings highlight that ignoring this strong BVOC-NO_x-O₃ interaction, which is highly dependent on the reduction stage, can lead to significant biases in evaluating long-term air quality policies.

Plain Language Summary Expanding vegetation cover is a widely adopted strategy to enhance regional environments and support climate objectives. However, vegetation naturally emits BVOCs, which can react with pollutants from human activities to form harmful ground-level ozone. Our study utilized atmospheric chemistry models to assess the future air quality impacts of the increased vegetation in China's Beijing-Tianjin-Hebei region, alongside planned, deep reductions in anthropogenic emissions. The results reveal a complex, time-dependent interaction. Under the moderate emission reduction scenario for 2040, increased BVOCs from vegetation growth are projected to significantly exacerbate ozone pollution, offsetting nearly half the air quality benefits gained from emission controls. Conversely, under the deep emission reduction scenario for 2060, this adverse effect is substantially diminished. This research highlights the necessity of strategically coordinating greening policies with emission control timelines to achieve synergistic improvements in future air quality.

1. Introduction

Ozone (O₃) is a major atmospheric pollutant that poses significant threats to both human health and crop yields (Hua et al., 2025; S. Li et al., 2025; Yang et al., 2025). Biogenic volatile organic compounds (BVOCs) serve as important precursors for O₃ formation, which exhibit higher reactivity and generate O₃ more efficiently during photochemical processes compared to anthropogenic volatile organic compounds (AVOCs) (Di Carlo et al., 2004). Globally, BVOC emissions (424–591 Tg C yr^{−1}) substantially exceed AVOC emissions (139–163 Tg C yr^{−1}) (Duan et al., 2023). With ongoing climate warming and successful cuts in anthropogenic pollution, BVOCs play an increasingly important role in O₃ pollution processes (Gao et al., 2022; Wang et al., 2021; Wu et al., 2020; Ren et al., 2014). This trend is critical for the future; as anthropogenic emissions continue to fall, the relative contribution of BVOCs to ozone formation will shift dramatically.

In recent years, China has implemented effective measures to reduce atmospheric pollutant emissions, achieving significant progress in controlling O₃ pollution (Wang et al., 2023). However, as these reductions continue, the cost of further measures is becoming prohibitive (Liu, Zhang, et al., 2023; Xie et al., 2019), shifting attention toward the role of BVOCs in O₃ formation. Over the past few decades, the expansion of vegetation in China has

resulted in sustained increases in BVOC emissions (L. Y. Li & Xie, 2014; L. Li et al., 2021). Historical studies have confirmed, from multiple perspectives—including land cover changes (M. Li et al., 2015), meteorological conditions (L. Li et al., 2021), and leaf biomass variations (Cao et al., 2022)—that vegetation growth significantly contributes to BVOC emissions and subsequent O₃ concentration increases. On the path to carbon neutrality, anthropogenic emissions are set to decline rapidly. This shift may trigger nonlinear changes in how vegetation-derived VOCs contribute to O₃ pollution, creating an urgent need to investigate the underlying mechanisms and quantify their impact.

Current studies investigating BVOC emissions and their effects on O₃ concentrations under future pathways typically assume that vegetation cover remains unchanged. These studies focus primarily on the role of meteorological conditions (Liu et al., 2019; Makkonen et al., 2012; Sporre et al., 2019) and the influence of anthropogenic emission changes on the contribution of BVOC to O₃ formation (Gao et al., 2022; Liu et al., 2025). The quantification of vegetation growth as a driving factor remains inadequate, with only limited studies incorporating vegetation changes. For instance, Liu et al. (2022) projected a 50% increase in China's forest cover and LAI, assessing the subsequent impacts on BVOC emissions and air pollutants. Following urban planning, Gu et al. (2021) projected the tree cover fraction to be 36% for 2050, while Schlaerth et al. (2023) increased the proportion of vegetation cover in the urban pervious land cover by 50% by 2045, to evaluate the differences in current and future O₃ responses in Los Angeles under combined changes in anthropogenic emission reductions and meteorological conditions. However, a critical gap remains: these analyses are primarily confined to a single future year, preventing a dynamic, multi-year understanding of how O₃ levels will evolve as both biogenic and anthropogenic emissions shift over time. Furthermore, incorporating the spatial heterogeneity and long-term trajectory of future vegetation change remains a significant challenge in regional air quality modeling.

Consequently, this study aims to investigate how BVOC emissions will dynamically affect regional O₃ pollution under future scenarios of deep anthropogenic emission cuts and significant vegetation growth using several numerical simulations. We predict future vegetation changes and use a chemical transport model to quantify resulting changes in BVOC emission patterns and evaluate the contribution of increased BVOC emissions to regional O₃ pollution. Finally, we analyze how the sensitivity of O₃ formation to BVOCs evolves dynamically as anthropogenic emissions decline. This study will clarify the extent to which natural emissions may offset the benefits of anthropogenic emission controls, filling a critical gap in our ability to project future air quality.

2. Data and Methods

2.1. Vegetation Growth Scenario

This study projects future vegetation changes by assessing two key components separately: the expansion of urban green space and variations in the Leaf Area Index (LAI) across urban and rural areas. We assume the expansion of urban green space follows a logistic growth pattern, stabilizing at an upper bound set by urban spatial constraints.

While large-scale land cover projections drive regional dynamics, they introduce significant limitations for localized urban green spaces. Standard land cover products often severely underestimate high-resolution urban vegetation. Ma et al. (2022) demonstrated that even 10 m resolution Land use and land cover data missed approximately half of the actual urban tree area compared to detailed surveys. Additionally, future land cover projections primarily emphasize urban expansion and often omit localized greening policies (Woodman et al., 2026; T. Zhang et al., 2023). To prevent the underestimation of biogenic emissions, this study utilizes a logistic growth model based on official statistical data to accurately capture the policy-driven trajectories. The logistic model depicts resource-limited growth as an S-shaped curve that levels off at carrying capacity (Bertsimas & King, 2017; Law et al., 2003; Sakanoue, 2007). Its application has since expanded to ecological and environmental fields (R. Cao et al., 2015; El-Rawy et al., 2022; Huang et al., 2021). By formulating the model's equation and optimizing its parameters, we will fit a logistic growth curve to project future urban green space coverage.

$$A_i = \frac{K_i}{1 + C_i e^{-r_i x}} \quad (1)$$

In this model, i denotes city, A denotes the urban green space coverage area and x is the time variable (year). The parameter K denotes the model's predicted saturation value for urban green space which is the asymptote that A approaches as the time variable x approaches infinity. r denotes the growth rate parameter. A higher r -value signifies a more rapid expansion of green space toward the saturation point (K). Finally, C is a constant parameter related to the initial conditions. Data on urban green space coverage for cities in the Beijing-Tianjin-Hebei region (BTH) from 1999 to 2022 were sourced from the China Urban Construction Statistical Yearbook series (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2007–2023). For future plant functional type distributions, the fractional coverage is scaled proportionally according to the specific logistic growth rate of urban green space projected for each city.

Changes in urban vegetation are more influenced by anthropogenic factors than those in rural areas, creating distinct spatiotemporal patterns (Jin et al., 2024; Z. Zhang et al., 2023; T. Zhou et al., 2023). Given this distinction, this study analyzes LAI trends in urban and rural areas separately. We quantified the interannual change in LAI from 1999 to 2022 across 13 cities in the BTH region using linear regression, as shown in Equation 2. The sustained increase in leaf area index through 2060 reflects the continuous crown volume expansion and biological maturation of young trees, representing the ecological time lag between initial spatial planting and full canopy maturity as supported by Moser et al. (2015).

$$L_i = \beta_i x + \alpha_i \quad (2)$$

where i denotes city, L denotes mean LAI value, x is the time variable (year), β denotes the average annual growth rate of LAI, and α is a constant. For cities where the trend was not statistically significant, we assigned the average LAI growth rate of the entire BTH region. Urban boundaries were defined using the Global Artificial Impervious Area (GAIA) data set from Gong et al. (2020) (see Figure S1 in Supporting Information S1). LAI data were sourced from the MODIS LAI product (MCD15A2H) at a 500m spatial resolution, provided by the NASA LAADS DAAC (Myneni et al., 2021).

2.2. Atmospheric Chemistry Modeling

2.2.1. WRF-Chem

Surface O_3 concentrations over the BTH region were simulated using WRF-Chem v3.9.1.1 (Mesoscale and Microscale Meteorology Laboratory, 2017) for the first half of July 2019. July is a typical period for both BVOC emissions and severe ozone pollution in our study region (Gao et al., 2022; Wu et al., 2020; Yang et al., 2024; Y. Zhang et al., 2025). The model was configured with nested domains: an outer domain covering eastern China (22.4°–47.3°N, 105.6°–124.4°E) at a 27 km resolution, and an inner domain focused on the BTH region (35.8°–43.3°N, 112.6°–120.4°E) at a 9 km resolution (Figure 1). WRF-Chem is an open-source regional model that fully couples atmospheric chemistry with meteorology. It simulates key processes such as pollutant emissions, transport, diffusion, deposition, photolysis, and gas- and aerosol-phase chemistry, and is widely used for studying O_3 pollution. In this study, initial and boundary meteorological conditions were derived from the ERA5 data set from the European Centre for Medium-Range Weather Forecasts (ECMWF) (ECMWF, 2019). Biogenic emissions were calculated online using the Model of Emissions of Gases and Aerosols from Nature (MEGAN) embedded within the WRF-Chem framework. This module estimates hourly emissions for 138 BVOC species based on the Guenther et al. (2006) algorithms. A key advantage of this online coupling is that MEGAN is directly driven by the real-time meteorological variables simulated by WRF (e.g., temperature, downward shortwave radiation, and soil moisture) and vegetation inputs (PFT distributions and LAI), ensuring that BVOC emission rates respond dynamically to changing environmental conditions at each time step. Anthropogenic emissions for 2019 were sourced from the Multi-resolution Emission Inventory for Climate and air pollution research (MEIC v1.4), developed by Tsinghua University (Geng et al., 2024). Future emissions were based on the “On-time Peak, Net-zero Clean Air” scenario from the Dynamic Projection model for Emissions in China (DPEC v1.2) (Cheng et al., 2023). Biomass burning emissions were incorporated from the Fire INventory from NCAR (FINN) (Wiedinmyer & Emmons, 2022; Wiedinmyer et al., 2023). The chemical initial and boundary conditions for all simulations, including the future scenarios for 2040 and 2060, were derived from the Community Atmosphere Model with Chemistry (CAM-Chem) model outputs (Buchholz et al., 2019) for the year 2019 and kept constant. This approach was specifically chosen to strictly isolate the regional air quality impacts of

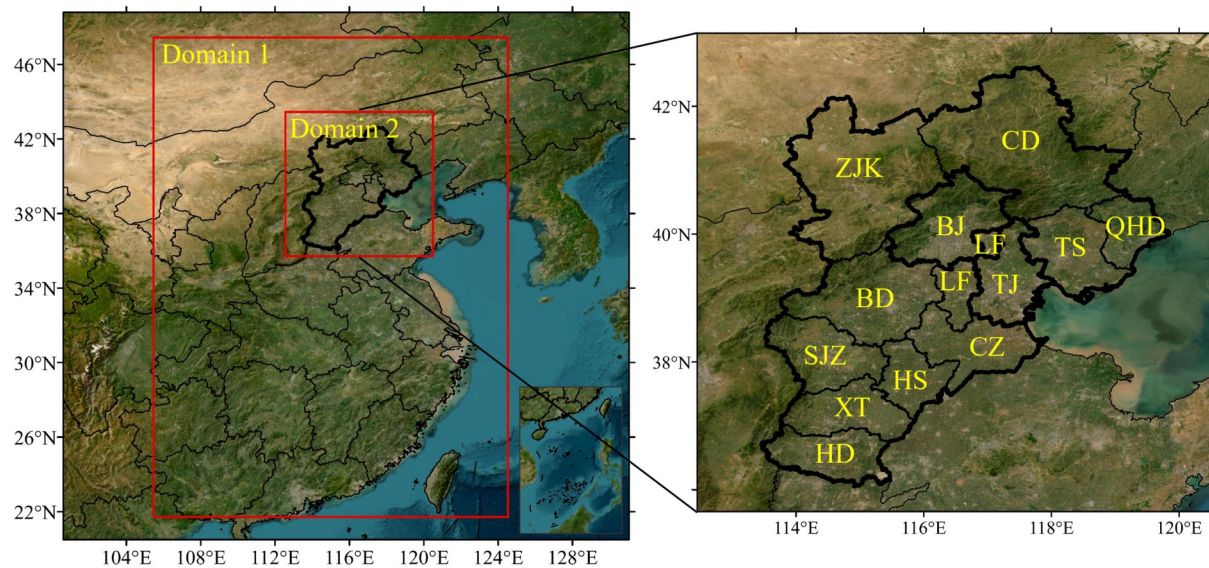


Figure 1. Study area. Abbreviations: ZJK: Zhangjiakou, CD: Chengde, BJ: Beijing, TS: Tangshan, QHD: Qinhuangdao, BD: Baoding, LF: Langfang, TJ: Tianjin, SJZ: Shijiazhuang, HS: Hengshui, CZ: Cangzhou, XT: Xingtai, HD: Handan.

domestic anthropogenic emission cuts and vegetation growth. The key physical and chemical schemes selected for this study are summarized in Table S1 of Supporting Information S1.

We evaluated the model's performance against observational data from the Beijing-Tianjin-Hebei (BTH) region. Hourly O_3 concentrations from 80 monitoring stations were sourced from the China National Environmental Monitoring Centre (CNEMC). Meteorological data from 13 stations were obtained from the National Climatic Data Center (NCDC) of the U.S. National Oceanic and Atmospheric Administration (NOAA). We performed an evaluation comparing simulated and observed O_3 concentrations, 2-m air temperature, 10-m wind speed, and relative humidity. The evaluation metrics included the correlation coefficient (R), mean bias (MB), and root mean square error (RMSE). As detailed in Figure S2 of Supporting Information S1, the model showed good agreement with these observations.

2.2.2. Scenario Design

We designed seven simulation scenarios (Table 1) to disentangle the independent and combined effects of vegetation growth and anthropogenic emission reductions on O_3 concentrations. All simulations were driven by identical meteorological conditions from the 2019 study period. The Base scenario serves as the benchmark, using actual vegetation and emission data from 2019. The impact of vegetation growth alone is determined by comparing the Vegetation Growth Only scenarios to the Base scenario, while the effect of emission reductions is quantified by comparing the Emission Cuts Only scenarios to the Base. The combined influence of both factors is assessed by comparing the Combined Scenario scenarios to the Base. Furthermore, to isolate the specific

contribution of vegetation growth under future emission conditions—a factor often overlooked in previous research—we subtract the results of an Emission Cuts Only scenario from its corresponding Combined Scenario (e.g., Combined Scenario 2040 – Emission Cuts Only 2040).

Table 1
Description of Simulation Scenarios

Scenario	Vegetation	Anthropogenic emission
Base	2019	MEIC (2019)
Vegetation Growth Only 2040	2040	MEIC (2019)
Vegetation Growth Only 2060	2060	MEIC (2019)
Emission Cuts Only 2040	2019	DPEC (2040)
Emission Cuts Only 2060	2019	DPEC (2060)
Combined Scenario 2040	2040	DPEC (2040)
Combined Scenario 2060	2060	DPEC (2060)

3. Results

3.1. Projected Vegetation Growth

Our model accurately simulates the historical expansion of urban green space in the BTH region from 1999 to 2022 (Figure 2a). The simulation demonstrates an excellent fit with observations ($R = 0.99$, $NMB = -0.1\%$) and aligns with the temporal dynamics reported in previous studies (Chen et al., 2025; Feng et al., 2025). This confirms that the simulation successfully

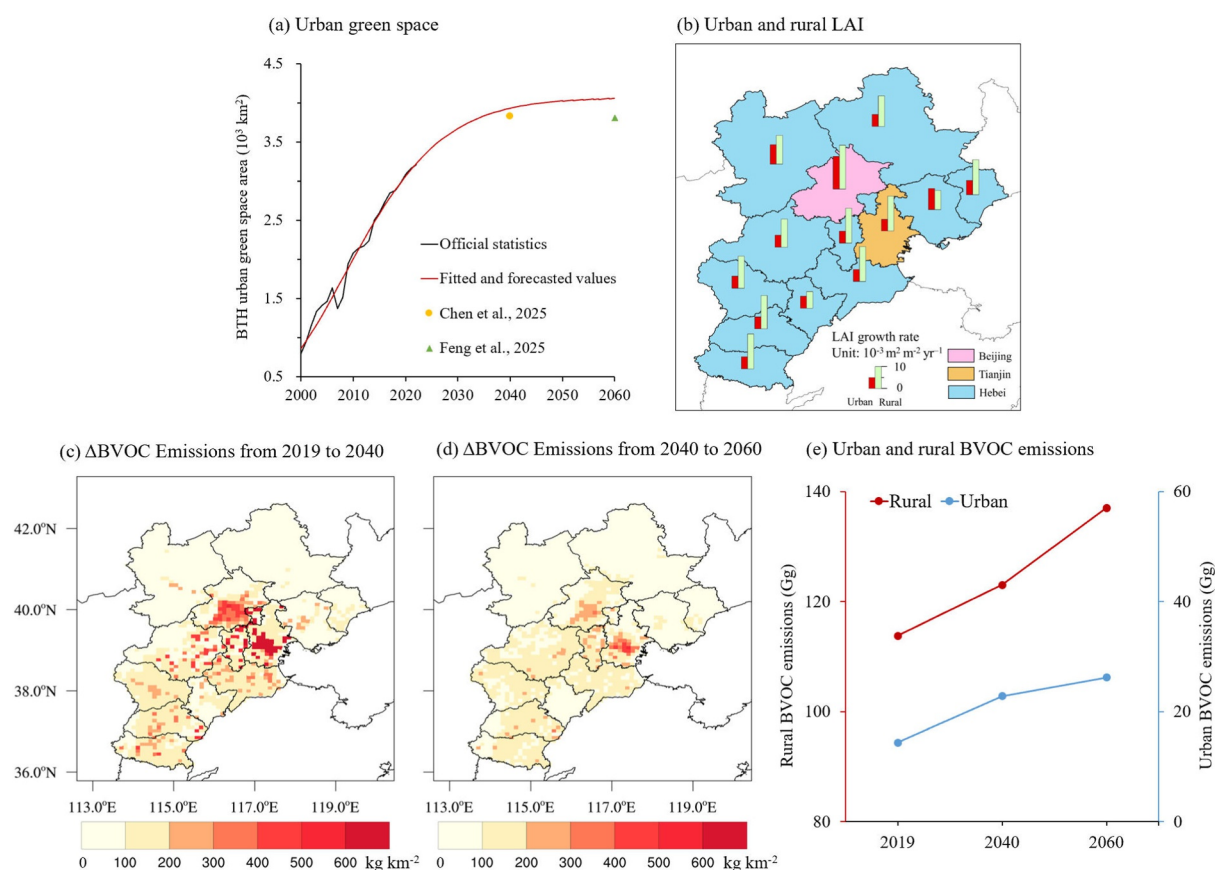


Figure 2. Projected changes in vegetation and their impact on BVOC emissions in the Beijing-Tianjin-Hebei (BTH) region, showing: (a) historical and projected urban green space area based on a fitted logistic growth curve; (b) projected annual rate of change in LAI for urban and rural areas; (c, d) projected changes in BVOC emission density for the period from 2019 to 2040 and from 2040 to 2060; and (e) a comparison of total BVOC emissions from urban and rural areas for 2019, 2040, and 2060.

captures the temporal dynamics of urban green space expansion recorded in the China Urban Construction Statistical Yearbook and aligns with the historical trends reported in previous studies. Our projections indicate that the total urban green area in the BTH region is projected to approach saturation around 2040 (at $3.9 \times 10^3 \text{ km}^2$) and slowly reach $4.1 \times 10^3 \text{ km}^2$ by 2060. This represents a 36.5% increase from 2019, corresponding to an average annual growth rate of $0.9\% \text{ yr}^{-1}$. Detailed projections of urban green space for all BTH cities are provided in Table S2 of Supporting Information S1.

Among individual cities, Tianjin is projected to have the largest expansion, reaching 884.5 km^2 by 2060, growing to 2.1 times its 2019 level. This rapid growth is likely due to Tianjin's large available land area and relatively low initial green coverage. In contrast, the urban green area in Tangshan is projected to remain stable. This is consistent with observational data showing that its green space expansion has already plateaued since 2010. Detailed statistical metrics and projections for all BTH cities are provided in Figure S3 and Table S2 of Supporting Information S1, respectively.

Across the BTH region, the average Leaf Area Index (LAI) grew at a rate of $13.6 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$. This rate is consistent with low-emission pathway scenarios ($2.8\text{--}15.7 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$) reported by H. Li et al. (2024). However, this regional average masks distinct trends between urban and rural areas (Figure 2b), which we analyzed separately due to the strong influence of anthropogenic activity on urban vegetation (Jin et al., 2024; Z. Zhang et al., 2023; T. Zhou et al., 2023). Specifically, LAI increased at a rate of $3.3 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$ in urban areas and $14.2 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$ in rural areas, respectively.

In urban areas, Beijing and Tangshan showed the most rapid greening, with annual LAI increases of 15.0 and $10.0 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$, respectively. The analysis of rural areas revealed even more dynamic changes. For instance, rural Beijing's LAI grew at $20.7 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$, a rate higher than its urban core. Similarly, rural

Xingtai experienced significant LAI growth ($15.8 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$, $p = 0.003$), which contrasted sharply with the weak positive trend in its urban center. Detailed fitted results for all cities are presented in Figures S4, S5 and Table S3 of Supporting Information S1.

3.2. BVOC Emission Changes Induced by Vegetation Growth

Our simulations estimate that total BVOC emissions in the BTH region reached 128.2 Gg in July 2019. This figure falls well within the 95.0–175.2 Gg range reported by previous studies (Cai et al., 2024; A. Li et al., 2023; L. Li et al., 2023; Qi et al., 2022; Xia & Xiao, 2019). Spatially, emissions were highest in the northern BTH and were predominantly from rural sources (Figure S6a). Urban areas contributed a total of 14.4 Gg, with the urban core of Beijing being the largest single urban source (3.4 Gg). In terms of chemical composition, isoprene was the largest contributor (35.4%), followed by oxygenated VOCs (30.1%), other VOCs (27.2%), and terpenes (7.2%) (Figure S6b in Supporting Information S1).

We project that future vegetation growth will substantially boost BVOC emissions across the BTH region (Figures 2c and 2d). Total emissions are expected to climb by 17.7 Gg (13.8%) by 2040 and by 35.1 Gg (27.4%) by 2060, relative to 2019 levels. Urban areas are expected to contribute 8.4 and 11.8 Gg to these increases in 2040 and 2060, respectively, raising their average emission density by 368.6 kg km^{-2} and 512.6 kg km^{-2} . The largest change is projected for Tianjin, reflecting its significant potential for future green space expansion.

Our temporal analysis reveals a shift in the primary source of BVOC emission increases. Initially, from 2019 to 2040 (Figure 2e), urban (8.4 Gg) and rural (9.2 Gg) areas are projected to contribute almost equally to the overall increase. However, this balance shifts dramatically after 2040 as urban green space nears its saturation point. In the subsequent period (2040–2060), the increase from urban areas (3.4 Gg) is projected to be just 24.3% of that from rural areas. This indicates that long-term growth in regional BVOC emissions will be overwhelmingly driven by rural vegetation.

3.3. Nonlinear Response of O₃ Concentration to Vegetation Growth Under Anthropogenic Emission Reduction Pathway

We quantified the impacts of anthropogenic emission reductions and vegetation-driven BVOC increases on future O₃ concentrations using WRF-Chem sensitivity experiments (Figure 3). With BVOC emissions fixed at 2019 levels, cuts in anthropogenic emissions alone will substantially decrease maximum daily 8-hour average (MDA8) O₃. Driven by a 51.9% reduction in anthropogenic NO_x and a 32.5% reduction in anthropogenic VOCs compared to the 2019 baseline, regional MDA8 O₃ is projected to fall by 7.8 ppb by 2040. By 2060, as the reductions in anthropogenic NO_x and VOCs deepen to 81.6% and 54.1% respectively, the MDA8 O₃ decrease becomes more pronounced, deepening to 13.7 ppb. The detailed emission reduction trajectories are illustrated in Figure S7 of Supporting Information S1. Consistent with previous research, the O₃ decrease was less pronounced in areas with high emission intensity (Figures 3a and 3b) (Hou et al., 2023; Z. Liu et al., 2021; Liu, Wild, et al., 2023; Weng et al., 2023).

However, our simulations show that increased BVOC emissions from vegetation growth will partially offset these gains, although this effect diminishes over time. In 2040, vegetation growth is projected to increase regional MDA8 O₃ by 2.5 ppb (3.5 ppb in urban areas), counteracting 33.1% (47.0% in urban areas) of the benefit from emission controls. This offsetting effect weakens to only 0.5 ppb regionally (1.0 ppb in urban areas) by 2060, negating a mere 3.6% (7.0% in urban areas) of the gains from emission cuts. This diminishing influence of BVOCs demonstrates a fundamental shift in atmospheric chemistry. The greater O₃ impact in urban areas is due to higher NO_x densities, which enhance O₃ production from BVOC precursors (Bell, 2004; Fitzky et al., 2019; Travis et al., 2016; Xu et al., 2025). While the spatial pattern of the O₃ increase from vegetation followed the pattern of the BVOC emission increase (Figures 3c and 3d), the magnitude of the effect changed over time. The sharp decline in the O₃ response to BVOCs by 2060 indicates a significant reduction in O₃ sensitivity to BVOCs. This shift is driven by the substantial changes in anthropogenic emissions. Anthropogenic NO_x emissions in the BTH region will decrease sharply from 184.5 Gg in 2019 to 88.8 Gg in 2040, and further to 33.9 Gg by 2060. Although anthropogenic VOCs are also projected to decline (from 181.6 Gg in 2019 to 83.3 Gg in 2060), the disproportionately larger reduction in NO_x shifts the BTH region into a strongly NO_x-limited chemical regime (Y. Liu et al., 2024). To better elucidate the underlying photochemical shifts, we evaluated the regional VOCs to NO_x emission ratios (Figure S8 in Supporting Information S1). The calculated emission ratio rises from 1.7 in the 2019

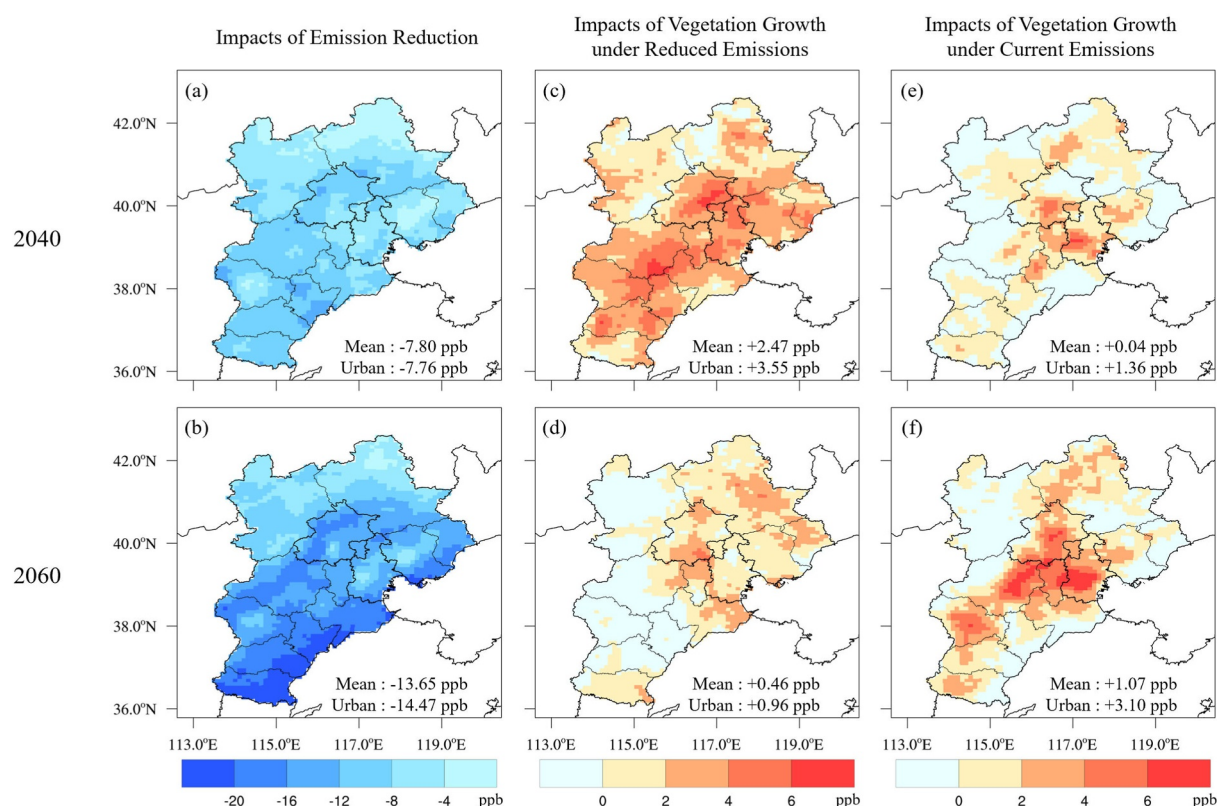


Figure 3. Simulated impacts on MDA8 O₃ concentrations, illustrating: (a, b) O₃ changes due solely to anthropogenic emission reductions in 2040 and 2060, respectively; (c, d) O₃ changes resulting from increased BVOC emissions from vegetation growth for the same years; and (e, f) the projected contribution of vegetation growth to MDA8 O₃ in 2040 and 2060 under the current anthropogenic emissions scenario.

baseline to 3.0 in 2040, and further escalates to 7.3 by 2060. This significant upward trajectory indicates the transition of regional ozone chemistry. Driven by the combined effects of stringent anthropogenic NO_x reductions and continuous increases in BVOCs, the region shifts toward a NO_x-limited regime by 2060.

While vegetation growth led to increased MDA8 O₃ in all BTH cities in 2040, a remarkable reversal is projected by 2060 (Table S4 in Supporting Information S1). In this future scenario, vegetation growth is expected to lower MDA8 O₃ concentrations in several cities, such as Hengshui (−1.9 ppb) and Xingtai (−1.5 ppb). This reversal is driven by the projected sharp decline in NO_x emissions by 2060 (−81.6% from 2019 levels), which shifts the region into a strongly NO_x-limited O₃ formation regime (G. Chen et al., 2024; Cheng et al., 2023). Under this condition, the large BVOC increases in major urban centers like Beijing and Tianjin intensify hotspots of radical cycling that efficiently sequester the scarce regional NO_x to produce O₃ locally. However, this process reduces the rural availability of NO_x, suppressing their O₃ production and leading to the observed decreases (Malashock et al., 2022; Sun et al., 2024). This spatial heterogeneity demonstrates that under future low-NO_x conditions, the uneven distribution of BVOC emissions can lead to complex and counterintuitive O₃ responses. Our findings highlight a critical limitation of linear thinking: in strongly NO_x-limited regimes, historical air quality management experiences may not be a reliable guide for predicting the outcomes of deep emission cuts.

To understand the changing sensitivity of O₃ to BVOCs, we simulated a fixed emissions scenario where anthropogenic emissions were held at 2019 levels while only vegetation grew (Figures 3c and 3f). By 2060, regional MDA8 O₃ increased by only 1.1 ppb (3.1 ppb in urban areas). A key finding, however, is that mid-term (2040) anthropogenic emission reductions paradoxically amplify the O₃ increase from vegetation growth (Figure 4). Under the combined scenario (Combined Scenario), the O₃ increase attributable to vegetation growth (+2.5 ppb regionally, +3.5 ppb in urban areas) was substantially higher than when emissions were not cut (Vegetation Growth Only scenario: +0.04 ppb regionally, +1.4 ppb in urban areas). This amplification occurs because moderate NO_x reductions shift the chemical regime into a transitional state that is highly sensitive to

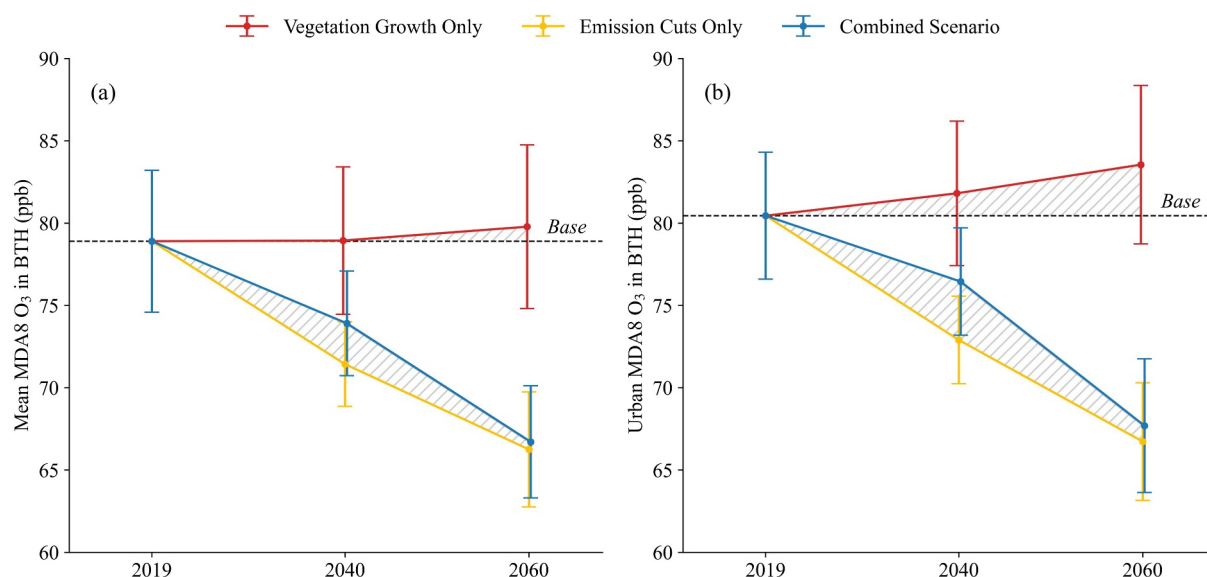


Figure 4. Temporal changes in summer MDA8 O₃ under different future pathways. The figure shows average concentrations for (a) the entire BTH region and (b) urban areas only. Lines represent different pathways: vegetation growth with constant 2019 emissions (Vegetation Growth Only, red); emission cuts with constant 2019 vegetation (Emission Cuts Only, yellow); and the combined scenario with both changes (Combined Scenario, blue). The 2019 baseline concentration is shown as a black dashed line. The gray hatched area highlights the additional O₃ resulting from vegetation growth. Error bars indicate spatial standard deviations.

BVOCs. O₃ responds nonlinearly to progressive NO_x reductions, increasing toward a maximum at the transition ridge before declining under NO_x-limited conditions (Z. Liu et al., 2021; Zeng et al., 2022; Liu et al., 2025). In our simulations, the 2040 background is closer to this ridge, strengthening the O₃ response to the same BVOC increase, whereas stronger NO_x limitation in 2060 weakens this response.

Changes in O₃, NO_x, and OH concentrations across simulation scenarios elucidate the nonlinear photochemical interactions, as illustrated in Figure S9 of Supporting Information S1. During the daytime peak hours from 12:00 to 18:00, the 2040 combined scenario demonstrates that abundant BVOCs consume OH, decreasing its levels from 3.2×10^{-1} ppt to 3.1×10^{-1} ppt compared to the Emission Cuts Only scenario. The concurrent oxidation of biogenic precursors converts NO to NO₂, driving the daytime average O₃ from 68.7 ppb up to 70.8 ppb. This dynamic shifts by 2060. Driven by deep anthropogenic cuts, daytime NO₂ plummets to 0.4 ppb. Under this severe NO_x limitation, although expanding BVOCs continue to consume OH, dropping its levels from 2.4×10^{-1} ppt to 2.2×10^{-1} ppt, the lack of NO_x prevents O₃ production. Consequently, daytime O₃ barely increases, shifting from 62.1 to 62.3 ppb. During the nighttime and early morning from 0:00 to 6:00, future O₃ concentrations rise by 3.4–4.2 ppb compared to the 2019 baseline, driven by weakened NO titration. In 2040, enhanced biogenic emissions increase NO₂ and NO levels by 11.5% and 21.1% respectively. This phenomenon stems from BVOCs competing for OH, which suppresses the conversion of NO₂ to HNO₃ (Qu et al., 2021; Wang et al., 2019).

However, the synergistic relationship between anthropogenic emission reductions and the O₃-forming potential of vegetation reverses with the deep, long-term (2060) emission cuts required for carbon neutrality. By 2060, the O₃ contribution from vegetation under the combined scenario (+0.5 ppb regionally, +1.0 ppb in urban areas) was much lower than in the no-cuts scenario (+1.1 ppb regionally, +3.1 ppb in urban areas). This occurs because the massive decline in NO_x availability pushes the region into a strongly NO_x-limited regime, where the capacity for O₃ formation is severely constrained, regardless of BVOC levels. Ultimately, accounting for vegetation growth alters the projected trajectory of O₃ decline. When vegetation is considered, the rate of O₃ reduction is significantly slower before 2040. Our results reveal a critical nonlinear relationship: as anthropogenic NO_x is progressively cut, the sensitivity of summer O₃ to rising BVOC emissions first increases and then decreases. This evolving sensitivity is a crucial consideration for long-term air quality management in a greening world.

4. Conclusions

To assess the dynamic impacts of BVOC emissions on regional O₃ pollution within future scenarios characterized by deep anthropogenic emission cuts and significant vegetation growth, we employed statistical models and the WRF-Chem atmospheric chemical transport model to project future vegetation coverage expansion and LAI growth, evaluating their impacts on summer BVOC emissions and O₃ concentrations in BTH region. The results demonstrate that vegetation growth, a factor often overlooked, plays a critical and nonlinear role in shaping future O₃ pollution dynamics under ambitious emission reduction pathways. We project that urban green space in the BTH region will increase by 36.5% by 2060 compared to 2019, approaching saturation around 2040, while the average LAI is expected to grow at $13.6 \times 10^{-3} \text{ m}^2 \text{ m}^{-2} \text{ yr}^{-1}$. This greening is projected to increase regional BVOC emissions by 35.1 Gg by 2060, with urban areas contributing 11.8 Gg of this increase. The impact of these rising BVOC emissions on O₃ is highly dependent on the level of anthropogenic emissions. In 2040, increased BVOCs are projected to offset the benefits of emission controls by a substantial margin (33.1% regionally, 47.0% in urban areas). However, as deep emission cuts create a strongly NO_x-limited environment by 2060, this offsetting effect weakens dramatically (to 3.6% regionally and 7.0% in urban areas). This reveals a critical nonlinear evolution: the sensitivity of O₃ to BVOCs first increases under moderate NO_x cuts, and then decreases under deep cuts. Consequently, vegetation growth reverses the O₃ reduction pattern from initially rapid to slow.

Our study has limitations that underscore the need for future research. First, our projections rely on static basal emission factors. However, this assumption introduces uncertainty, as recent studies indicate that vegetation composition and physiological traits are likely to evolve under a warming climate (Higgins et al., 2023; Ren et al., 2024; Zhang et al., 2022). Second, emission uncertainties were evaluated using 100,000 Monte Carlo simulations with literature-based ranges of 22% variations for AVOC (M. Li et al., 2019), 95.0–175.2 Gg for July 2019 BVOC emissions, applied as relative scaling factors to each scenario (Cai et al., 2024; A. Li et al., 2023; L. Li et al., 2023; Qi et al., 2022; Xia & Xiao, 2019), and −13% to +49% for NO_x (Zhao et al., 2011, 2018). The resulting 95% intervals of the VOCs/NO_x ratio were 1.2–2.0, 2.1–3.6, and 5.0–8.7 for 2019, 2040, and 2060, respectively. The simulated VOCs/NO_x ratio for 2040 is 3.0. These results are consistent with an emission-reduction trajectory that passes through an intermediate O₃-ridge region. These uncertainties could not alter the conclusion that the BVOC-induced O₃ enhancement is strongest near the intermediate stage and weakens with further NO_x reductions, although they may shift the timing of the transition. Third, we employed fixed 2019 meteorological conditions to isolate the chemical impacts of vegetation changes. This approach excludes the direct amplification effect of future climate change on BVOC emission rates. As BVOC emissions typically increase exponentially with temperature (Moradi et al., 2025; Wang et al., 2025), the combined effect of vegetation expansion and climate warming would likely result in even higher emissions than reported here. To evaluate the potential amplification effect of future climate change, we conducted a sensitivity analysis by increasing the surface temperature in our model by 1°C while keeping other variables constant. Our results indicate that this warming effect is relatively minor compared to the impact of vegetation expansion, as a 1°C increase leads to a 6.1% increase in regional BVOC emissions. This aligns with Gu et al. (2021), who projected that meteorological changes under the RCP8.5 scenario would increase BVOC emissions by 4.6% by 2050. Given that future warming would further amplify BVOC emissions, excluding dynamic climate variables does not alter our core conclusions. Future work integrating long-term dynamic ecological and climate models will be crucial for refining these projections. Finally, although the 9 km resolution is widely adopted for regional simulations across urban agglomerations, it may smooth out subgrid emission gradients and introduce local uncertainties in ozone chemistry. Future studies utilizing finer grid resolutions with correspondingly high-resolution emission inventories are needed.

Our findings show that ignoring the complex interactions between vegetation growth and emission reductions can lead to significant biases when evaluating long-term air quality policies. Given that the impact of BVOCs on O₃ pollution is strongly nonlinear with respect to anthropogenic NO_x emission levels, future air quality management and urban planning policies must move beyond a singular focus on emission reduction targets to strategically incorporate the deployment of green infrastructure. This requires coordinating urban greening goals with long-term deep NO_x reduction targets and optimizing the spatial layout of green spaces based on nonlinear chemical sensitivity. Given that isoprene is the predominant contributor to O₃ formation, we strongly recommend the strategic selection and planting of low-isoprene-emitting tree species during future urban green space expansion. By optimizing the vegetation composition, policymakers can maximize the ecological benefits of urban greening while effectively minimizing the unintended chemical offset to regional anthropogenic emission control efforts.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The source code of WRF-Chem is available at <https://www2.mmm.ucar.edu/wrf/users/>. MEIC (version 1.4) and DPEC (version 1.2) emission data can be accessed from <http://meicmodel.org.cn>. ERA5 meteorological data from ECMWF are provided at <https://gdex.ucar.edu/datasets/d633000/dataaccess/#>. Simulations by CAM-chem can be accessed from <https://www.acom.ucar.edu/cam-chem/cam-chem.shtml>. Surface measurement data of O₃ data are available at <https://quotsft.net/air/>. Meteorological data from NCDC can be accessed from <https://www.ncei.noaa.gov/data/global-summary-of-the-day/access/>. WRF-Chem preprocessing tools mozbc, fire_emiss and bio_emiss can be downloaded from <https://www.acom.ucar.edu/wrf-chem/download.shtml>.

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References

- Bell, M. (2004). Sensitivity analysis of tropospheric ozone to modified biogenic emissions for the Mid-Atlantic region. *Atmospheric Environment*, 38(13), 1879–1889. <https://doi.org/10.1016/j.atmosenv.2004.01.012>
- Bertsimas, D., & King, A. (2017). Logistic regression: From art to science. *Statistical Science*, 32(3). <https://doi.org/10.1214/16-sts602>
- Buchholz, R. R., Emmons, L. K., & Tilmes, S., & The CESM2 Development Team. (2019). CESM2.1/CAM-chem instantaneous output for boundary conditions [Dataset]. *UCAR/NCAR - Atmospheric Chemistry Observations and Modeling Laboratory*. <https://doi.org/10.5065/NMP7-EP60>
- Cai, B., Cheng, H., & Kang, T. (2024). Establishing the emission inventory of biogenic volatile organic compounds and quantifying their contributions to O₃ and PM_{2.5} in the Beijing-Tianjin-Hebei region. *Atmospheric Environment*, 318, 120206. <https://doi.org/10.1016/j.atmosenv.2023.120206>
- Cao, J., Situ, S., Hao, Y., Xie, S., & Li, L. (2022). Enhanced summertime ozone and SOA from biogenic volatile organic compound (BVOC) emissions due to vegetation biomass variability during 1981–2018 in China. *Atmospheric Chemistry and Physics*, 22(4), 2351–2364. <https://doi.org/10.5194/acp-22-2351-2022>
- Cao, R., Chen, J., Shen, M., & Tang, Y. (2015). An improved logistic method for detecting spring vegetation phenology in grasslands from MODIS EVI time-series data. *Agricultural and Forest Meteorology*, 200, 9–20. <https://doi.org/10.1016/j.agrformet.2014.09.009>
- Chen, G., Liu, T., Chen, J., Xu, L., Hu, B., Yang, C., et al. (2024). Atmospheric oxidation capacity and O₃ formation in a coastal city of southeast China: Results from simulation based on four-season observation. *Journal of Environmental Sciences*, 136, 68–80. <https://doi.org/10.1016/j.jes.2022.11.015>
- Chen, J., Qiu, B., Chakraborty, T., Miao, X., Cao, Y., Li, L., et al. (2025). Contrasting effects of urbanization on vegetation between the Global South and Global North. *Nature Sustainability*, 8(4), 373–384. <https://doi.org/10.1038/s41893-025-01520-0>
- Cheng, J., Tong, D., Liu, Y., Geng, G., Davis, S. J., He, K., & Zhang, Q. (2023). A synergistic approach to air pollution control and carbon neutrality in China can avoid millions of premature deaths annually by 2060. *One Earth*, 6(8), 978–989. <https://doi.org/10.1016/j.oneear.2023.07.007>
- Di Carlo, P., Brune, W. H., Martinez, M., Harder, H., Leshner, R., Ren, X., et al. (2004). Missing OH reactivity in a forest: Evidence for unknown reactive biogenic VOCs. *Science*, 304(5671), 722–725. <https://doi.org/10.1126/science.1094392>
- Duan, C., Liao, H., Wang, K., & Ren, Y. (2023). The research hotspots and trends of volatile organic compound emissions from anthropogenic and natural sources: A systematic quantitative review. *Environmental Research*, 216, 114386. <https://doi.org/10.1016/j.envres.2022.114386>
- El-Rawy, M., Elsadek, W. M., & De Smedt, F. (2022). Flash flood susceptibility mapping in Sinai, Egypt using hydromorphic data, principal component analysis and logistic regression. *Water*, 14(15), 2434. <https://doi.org/10.3390/w14152434>
- European Centre for Medium-Range Weather Forecasts. (2019). ERA5 reanalysis (0.25 degree latitude-longitude grid) [Dataset]. *NSF National Center for Atmospheric Research*. updated monthly. <https://doi.org/10.5065/BH6N-5N20>
- Feng, R., Li, G., Alberti, M., Wang, F., Liu, S., & Yu, G. (2025). Optimizing urban greenspace landscapes to mitigate population exposure to extreme heat in 21st century Chinese cities. *Environmental Science & Technology*, 59(11), 5510–5520. <https://doi.org/10.1021/acs.est.4c11345>
- Fitzky, A. C., Sandén, H., Karl, T., Fares, S., Calfapietra, C., Grote, R., et al. (2019). The interplay between ozone and urban Vegetation—Bvoc emissions, ozone deposition, and tree ecophysiology. *Frontiers in Forests and Global Change*, 2, 50. <https://doi.org/10.3389/ffgc.2019.00050>
- Fu, D., Millet, D. B., Wells, K. C., Payne, V. H., Yu, S., Guenther, A., & Eldering, A. (2019). Direct retrieval of isoprene from satellite-based infrared measurements. *Nature Communications*, 10(1), 3811. <https://doi.org/10.1038/s41467-019-11835-0>
- Gao, Y., Ma, M., Yan, F., Su, H., Wang, S., Liao, H., et al. (2022). Impacts of biogenic emissions from urban landscapes on summer ozone and secondary organic aerosol formation in megacities. *Science of The Total Environment*, 814, 152654. <https://doi.org/10.1016/j.scitotenv.2021.152654>
- Geng, G., Liu, Y., Liu, Y., Liu, S., Cheng, J., Yan, L., et al. (2024). Efficacy of China's clean air actions to tackle PM_{2.5} pollution between 2013 and 2020. *Nature Geoscience*, 17(10), 987–994. <https://doi.org/10.1038/s41561-024-01540-z>
- Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., et al. (2020). Annual maps of global artificial impervious area (GAIA) between 1985 and 2018. *Remote Sensing of Environment*, 236, 111510. <https://doi.org/10.1016/j.rse.2019.111510>
- Gu, S., Guenther, A., & Faiola, C. (2021). Effects of anthropogenic and biogenic volatile organic compounds on Los Angeles air quality. *Environmental Science & Technology*, 55(18), 12191–12201. <https://doi.org/10.1021/acs.est.1c01481>
- Guenther, A., Karl, T., Harley, P., Wiedinmyer, C., Palmer, P. I., & Geron, C. (2006). Estimates of global terrestrial isoprene emissions using MEGAN (Model of Emissions of Gases and Aerosols from Nature). *Atmospheric Chemistry and Physics*, 6(11), 3181–3210. <https://doi.org/10.5194/acp-6-3181-2006>
- Higgins, S. I., Conradi, T., & Muhoko, E. (2023). Shifts in vegetation activity of terrestrial ecosystems attributable to climate trends. *Nature Geoscience*, 16(2), 147–153. <https://doi.org/10.1038/s41561-022-01114-x>

- Hou, X., Wild, O., Zhu, B., & Lee, J. (2023). Future tropospheric ozone budget and distribution over east Asia under a net-zero scenario. *Atmospheric Chemistry and Physics*, 23(24), 15395–15411. <https://doi.org/10.5194/acp-23-15395-2023>
- Hua, Q., Meng, X., Gong, J., Qiu, X., Shang, J., Xue, T., & Zhu, T. (2025). Ozone exposure and cardiovascular disease: A narrative review of epidemiology evidence and underlying mechanisms. *Fundamental Research*, 5(1), 249–263. <https://doi.org/10.1016/j.fmre.2024.02.016>
- Huang, D., Chi, H., Xin, F., Miyata, A., Kang, M., Liu, K., et al. (2021). Improved estimation of gross primary production of paddy rice cropland with changing model parameters over phenological transitions. *Ecological Modelling*, 445, 109492. <https://doi.org/10.1016/j.ecolmodel.2021.109492>
- Jin, Y., Wang, F., Zong, Q., Jin, K., Liu, C., & Qin, P. (2024). Spatial patterns and driving forces of urban vegetation greenness in China: A case study comprising 289 cities. *Geography and Sustainability*, 5(3), 370–381. <https://doi.org/10.1016/j.geosus.2024.03.001>
- Law, R., Murrell, D. J., & Dieckmann, U. (2003). Population growth in space and time: Spatial logistic equations. *Ecology*, 84(1), 252–262. [https://doi.org/10.1890/0012-9658\(2003\)084%255B0252:PGISAT%255D2.0.CO;2](https://doi.org/10.1890/0012-9658(2003)084%255B0252:PGISAT%255D2.0.CO;2)
- Li, A., Duan, W., Qi, H., & Cai, B. (2023). BVOCs emission inventory in the Beijing-Tianjin-Hebei region based on multiple models and data sources. *China Environmental Science*, 43(10), 5052–5061.
- Li, H., Zhou, Y., Zhao, X., Zhang, X., & Liang, S. (2024). A dataset of 0.05-degree leaf area index in China during 1983–2100 based on deep learning network. *Scientific Data*, 11(1), 1122. <https://doi.org/10.1038/s41597-024-03948-z>
- Li, L., Cao, J., & Hao, Y. (2023). Spatial and species-specific responses of biogenic volatile organic compound (BVOC) emissions to elevated ozone from 2014–2020 in China. *Science of The Total Environment*, 868, 161636. <https://doi.org/10.1016/j.scitotenv.2023.161636>
- Li, L., Zhang, B., Cao, J., Xie, S., & Wu, Y. (2021). Isoprenoid emissions from natural vegetation increased rapidly in eastern China. *Environmental Research*, 200, 111462. <https://doi.org/10.1016/j.envres.2021.111462>
- Li, L. Y., & Xie, S. D. (2014). Historical variations of biogenic volatile organic compound emission inventories in China, 1981–2003. *Atmospheric Environment*, 95, 185–196. <https://doi.org/10.1016/j.atmosenv.2014.06.033>
- Li, M., Song, Y., Liu, M., Yao, H., Huang, X., Wang, X., & Zhang, Y. (2015). Impacts of decadal variations in natural emissions due to land-cover changes on ozone production in southern China. *Tellus B: Chemical and Physical Meteorology*, 67(1), 27676. <https://doi.org/10.3402/tellusb.v67.27676>
- Li, M., Zhang, Q., Zheng, B., Tong, D., Lei, Y., Liu, F., et al. (2019). Persistent growth of anthropogenic non-methane volatile organic compound (NMVOC) emissions in China during 1990–2017: Drivers, speciation and ozone formation potential. *Atmospheric Chemistry and Physics*, 19(13), 8897–8913. <https://doi.org/10.5194/acp-19-8897-2019>
- Li, S., Gao, Y., Zhang, J., Hong, C., Zhang, S., Chen, D., et al. (2025). Mitigating climate change and ozone pollution will improve Chinese food security. *One Earth*, 8(2), 101166. <https://doi.org/10.1016/j.oneear.2024.12.002>
- Liu, S., Sahu, S. K., Zhang, S., Liu, S., Sun, Y., Liu, X., et al. (2022). Impact of climate-driven land-use change on O₃ and PM pollution by driving BVOC emissions in China in 2050. *Atmosphere*, 13(7), 1086. <https://doi.org/10.3390/atmos13071086>
- Liu, S., Xing, J., Zhang, H., Ding, D., Zhang, F., Zhao, B., et al. (2019). Climate-driven trends of biogenic volatile organic compound emissions and their impacts on summertime ozone and secondary organic aerosol in China in the 2050s. *Atmospheric Environment*, 218, 117020. <https://doi.org/10.1016/j.atmosenv.2019.117020>
- Liu, Y., Chen, T., Ma, Z., Li, Q., Gao, Y., Xue, L., & Wang, W. (2025). Variation of biogenic VOC contribution to ozone formation with reduced anthropogenic precursor emissions: Coupling online observation and future scenario simulation. *Science of The Total Environment*, 961, 178380. <https://doi.org/10.1016/j.scitotenv.2025.178380>
- Liu, Y., Tang, G., Wang, Y., Cheng, M., Gao, J., & Wang, Y. (2024). Spatiotemporal differences in tropospheric ozone sensitivity and the impact of “dual carbon” goal. *Science Bulletin*, 69(4), 422–425. <https://doi.org/10.1016/j.scib.2023.12.026>
- Liu, Z., Doherty, R. M., Wild, O., Hollaway, M., & O'Connor, F. M. (2021). Contrasting chemical environments in summertime for atmospheric ozone across major Chinese industrial regions: The effectiveness of emission control strategies. *Atmospheric Chemistry and Physics*, 21(13), 10689–10706. <https://doi.org/10.5194/acp-21-10689-2021>
- Liu, Z., Wild, O., Doherty, R. M., O'Connor, F. M., & Turnock, S. T. (2023). Benefits of net-zero policies for future ozone pollution in China. *Atmospheric Chemistry and Physics*, 23(21), 13755–13768. <https://doi.org/10.5194/acp-23-13755-2023>
- Liu, Z., Xiang, Y., Pan, Y., Zhang, T., Xu, W., & Li, L. (2024). Unveiling 3-D evolution and mechanisms of ozone pollution in Changzhou, China: Insights from LiDAR observations and modelling. *Environmental Pollution*, 359, 124556. <https://doi.org/10.1016/j.envpol.2024.124556>
- Liu, Z., Zhang, Y., Wang, Y., Jiang, F., Qi, Z., Cao, W., et al. (2023). Cost-Effectiveness of NO_x and VOC Co-operative controls for PM_{2.5} and O₃ mitigation in the context of China's carbon neutrality. *Environmental Science and Technology Letters*, 10(11), 1109–1116. <https://doi.org/10.1021/acs.estlett.3c00649>
- Ma, M., Gao, Y., Ding, A., Su, H., Liao, H., Wang, S., et al. (2022). Development and assessment of a high-resolution biogenic emission inventory from urban green spaces in China. *Environmental Science & Technology*, 56(1), 175–184. <https://doi.org/10.1021/acs.est.1c06170>
- Makkonen, R., Asmi, A., Kerminen, V.-M., Boy, M., Arneth, A., Guenther, A., & Kulmala, M. (2012). BVOC-aerosol-climate interactions in the global aerosol-climate model ECHAM5.5-HAM2. *Atmospheric Chemistry and Physics*, 12(21), 10077–10096. <https://doi.org/10.5194/acp-12-10077-2012>
- Malashock, D. A., DeLang, M. N., Becker, J. S., Serre, M. L., West, J. J., Chang, K.-L., et al. (2022). Estimates of ozone concentrations and attributable mortality in urban, peri-urban and rural areas worldwide in 2019. *Environmental Research Letters*, 17(5), 054023. <https://doi.org/10.1088/1748-9326/ac66f3>
- Mesoscale and Microscale Meteorology Laboratory. (2017). The Weather Research and Forecasting (WRF) Model (Version 3.9.1.1) [Software]. <https://doi.org/10.5065/D6MK6B4K>
- Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2007–2023). *China urban construction statistical Yearbook—2006–2022*. China Statistics Press.
- Moradi, A., Abera, T. A., Shayle, E. S., Muhammed, M. A., & Zeuss, D. (2025). Modeling long-term dynamics of biogenic volatile organic compounds (BVOCs) in Germany based on major precursors. *Environmental Science & Technology*, 59(9), 4587–4596. <https://doi.org/10.1021/acs.est.4c14418>
- Moser, A., Rötzer, T., Pauleit, S., & Pretzsch, H. (2015). Structure and ecosystem services of small-leaved lime (*Tilia cordata* Mill.) and black locust (*Robinia pseudoacacia* L.) in urban environments. *Urban Forestry & Urban Greening*, 14(4), 1110–1121. <https://doi.org/10.1016/j.ufug.2015.10.005>
- Myneni, R., Knyazikhin, Y., & Park, T. (2021). MODIS/Terra+Aqua leaf area Index/FPAR 8-Day L4 global 500m SIN grid V061 [Dataset]. *NASA Land Processes Distributed Active Archive Center*. <https://doi.org/10.5067/MODIS/MCD15A2H>
- Qi, H., Wang, X., Cheng, S., Cai, B., & Li, A. (2022). Estimation of BVOCs emissions from Beijing, Tianjin and Hebei from 2000 to 2020 and its temporal and spatial distribution characteristics. *China Environmental Science*, 42(4), 1501–1509.

- Qu, H., Wang, Y., Zhang, R., Liu, X., Huey, L. G., Sjostedt, S., et al. (2021). Chemical production of oxygenated volatile organic compounds strongly enhances boundary-layer oxidation chemistry and ozone production. *Environmental Science & Technology*, 55(20), 13718–13727. <https://doi.org/10.1021/acs.est.1c04489>
- Ren, Y., Ge, Y., Gu, B., Min, Y., Tani, A., & Chang, J. (2014). Role of management strategies and environmental factors in determining the emissions of biogenic volatile organic compounds from urban greenspaces. *Environmental Science & Technology*, 48(11), 6237–6246. <https://doi.org/10.1021/es4054434>
- Ren, Z., Liu, L., Yin, F., & Liu, X. (2024). Modelling analysis embodies drastic transition among global potential natural vegetations in face of changing climate. *Forest Ecosystems*, 11, 100180. <https://doi.org/10.1016/j.fecs.2024.100180>
- Sakanoue, S. (2007). Extended logistic model for growth of single-species populations. *Ecological Modelling*, 205(1–2), 159–168. <https://doi.org/10.1016/j.ecolmodel.2007.02.013>
- Schlaerth, H. L., Silva, S. J., & Li, Y. (2023). Characterizing ozone sensitivity to urban greening in Los Angeles under Current day and future anthropogenic emissions scenarios. *Journal of Geophysical Research: Atmospheres*, 128(20), e2023JD039199. <https://doi.org/10.1029/2023JD039199>
- Sporre, M. K., Blichner, S. M., Karset, I. H. H., Makkonen, R., & Berntsen, T. K. (2019). BVOC–aerosol–climate feedbacks investigated using NorESM. *Atmospheric Chemistry and Physics*, 19(7), 4763–4782. <https://doi.org/10.5194/acp-19-4763-2019>
- Sun, H. Z., Van Daalen, K. R., Morawska, L., Guillas, S., Giorio, C., Di, Q., et al. (2024). An estimate of global cardiovascular mortality burden attributable to ambient ozone exposure reveals urban-rural environmental injustice. *One Earth*, 7(10), 1803–1819. <https://doi.org/10.1016/j.oneear.2024.08.018>
- Travis, K. R., Jacob, D. J., Fisher, J. A., Kim, P. S., Marais, E. A., Zhu, L., et al. (2016). Why do models overestimate surface ozone in the Southeast United States? *Atmospheric Chemistry and Physics*, 16(21), 13561–13577. <https://doi.org/10.5194/acp-16-13561-2016>
- Wang, H., Wu, K., Liu, Y., Sheng, B., Lu, X., He, Y., et al. (2021). Role of heat wave-induced biogenic VOC enhancements in persistent ozone episodes Formation in Pearl River Delta. *Journal of Geophysical Research: Atmospheres*, 126(12), e2020JD034317. <https://doi.org/10.1029/2020JD034317>
- Wang, N., Liu, S., Xu, J., Wang, Y., Li, C., Xie, Y., et al. (2025). Climate-driven biogenic emissions alleviate the impact of human-made emission reductions on O₃ control in the Pearl River Delta region, southern China. *Atmospheric Chemistry and Physics*, 25(15), 8859–8870. <https://doi.org/10.5194/acp-25-8859-2025>
- Wang, N., Lyu, X., Deng, X., Huang, X., Jiang, F., & Ding, A. (2019). Aggravating O₃ pollution due to NO_x emission control in eastern China. *Science of The Total Environment*, 677, 732–744. <https://doi.org/10.1016/j.scitotenv.2019.04.388>
- Wang, Y., Zhao, Y., Liu, Y., Jiang, Y., Zheng, B., Xing, J., et al. (2023). Sustained emission reductions have restrained the ozone pollution over China. *Nature Geoscience*, 16(11), 967–974. <https://doi.org/10.1038/s41561-023-01284-2>
- Wei, L., Liu, R., Liao, C., Ouyang, S., Wu, Y., Jiang, B., et al. (2024). An observation-based analysis of atmospheric oxidation capacity in Guangdong, China. *Atmospheric Environment*, 318, 120260. <https://doi.org/10.1016/j.atmosenv.2023.120260>
- Wells, K. C., Millet, D. B., Payne, V. H., Deventer, M. J., Bates, K. H., De Gouw, J. A., et al. (2020). Satellite isoprene retrievals constrain emissions and atmospheric oxidation. *Nature*, 585(7824), 225–233. <https://doi.org/10.1038/s41586-020-2664-3>
- Weng, X., Li, J., Forster, G. L., & Nowack, P. (2023). Large modeling uncertainty in projecting decadal surface ozone changes over City clusters of China. *Geophysical Research Letters*, 50(9), e2023GL103241. <https://doi.org/10.1029/2023GL103241>
- Wiedinmyer, C., & Emmons, L. K. (2022). Fire Inventory from NCAR version 2 Fire Emission [Dataset]. *NSF National Center for Atmospheric Research*. updated irregularly. <https://doi.org/10.5065/XNPA-AF09>
- Wiedinmyer, C., Kimura, Y., McDonald-Buller, E. C., Emmons, L. K., Buchholz, R. R., Tang, W., et al. (2023). The Fire Inventory from NCAR version 2.5: An updated global fire emissions model for climate and chemistry applications. *Geoscientific Model Development*, 16(13), 3873–3891. <https://doi.org/10.5194/gmd-16-3873-2023>
- Woodman, T. L., Arendarczyk, B., Winkler, K., Henry, R. C., Eigenbrod, F., Burslem, D. F. R. P., et al. (2026). High-resolution land-use maps from 1960 to 2100. *One Earth*, 9(2), 101525. <https://doi.org/10.1016/j.oneear.2025.101525>
- Wu, K., Yang, X., Chen, D., Gu, S., Lu, Y., Jiang, Q., et al. (2020). Estimation of biogenic VOC emissions and their corresponding impact on ozone and secondary organic aerosol formation in China. *Atmospheric Research*, 231, 104656. <https://doi.org/10.1016/j.atmosres.2019.104656>
- Xia, C., & Xiao, L. (2019). Estimation of biogenic volatile organic compounds emissions in jing-jin-ji. *Acta Scientiae Circumstantiae*, 39(8), 3680–3689. <https://doi.org/10.13671/j.hjkxb.2019.0105>
- Xie, Q., Chen, W., Yuan, B., Huangfu, Y., He, X., Wu, L., et al. (2025). Significant but overlooked: The role of anthropogenic monoterpenes in ozone Formation in a Chinese megacity. *Environmental Science & Technology*, 59(16), 8085–8098. <https://doi.org/10.1021/acs.est.5c00001>
- Xie, Y., Dai, H., Zhang, Y., Wu, Y., Hanaoka, T., & Masui, T. (2019). Comparison of health and economic impacts of PM_{2.5} and ozone pollution in China. *Environment International*, 130, 104881. <https://doi.org/10.1016/j.envint.2019.05.075>
- Xu, J., Silver, B., Tang, R., Wang, N., Huang, X., Ding, A., & Arnold, S. R. (2025). A model assessment of the relationship between urban greening and ozone air quality in China: A study of three metropolitan regions. *npj Climate and Atmospheric Science*, 8(1), 184. <https://doi.org/10.1038/s41612-025-01054-4>
- Yang, Y., Zhou, Y., Wang, H., Li, M., Li, H., Wang, P., et al. (2024). Meteorological characteristics of extreme ozone pollution events in China and their future predictions. *Atmospheric Chemistry and Physics*, 24(2), 1177–1191. <https://doi.org/10.5194/acp-24-1177-2024>
- Yang, Z., Li, Z., Cheng, F., Lv, Q., Li, K., Zhang, T., et al. (2025). Two-decade surface ozone (O₃) pollution in China: Enhanced fine-scale estimations and environmental health implications. *Remote Sensing of Environment*, 317, 114459. <https://doi.org/10.1016/j.rse.2024.114459>
- Zeng, X., Gao, Y., Wang, Y., Ma, M., Zhang, J., & Sheng, L. (2022). Characterizing the distinct modulation of future emissions on summer ozone concentrations between urban and rural areas over China. *Science of The Total Environment*, 820, 153324. <https://doi.org/10.1016/j.scitotenv.2022.153324>
- Zhang, T., Cheng, C., & Wu, X. (2023). Mapping the spatial heterogeneity of global land use and land cover from 2020 to 2100 at a 1 km resolution. *Scientific Data*, 10(1), 748. <https://doi.org/10.1038/s41597-023-02637-7>
- Zhang, Y., Piao, S., Sun, Y., Rogers, B. M., Li, X., Lian, X., et al. (2022). Future reversal of warming-enhanced vegetation productivity in the Northern Hemisphere. *Nature Climate Change*, 12(6), 581–586. <https://doi.org/10.1038/s41558-022-01374-w>
- Zhang, Y., Ran, H., Guenther, A., Zhang, Q., George, C., Mellouki, W., et al. (2025). Improved modelling of biogenic emissions in human-disturbed forest edges and urban areas. *Nature Communications*, 16(1), 8064. <https://doi.org/10.1038/s41467-025-63437-8>
- Zhang, Z., Zhao, W., Liu, Y., & Pereira, P. (2023). Impacts of urbanisation on vegetation dynamics in Chinese cities. *Environmental Impact Assessment Review*, 103, 107227. <https://doi.org/10.1016/j.eiar.2023.107227>
- Zhao, Y., Nielsen, C. P., Lei, Y., McElroy, M. B., & Hao, J. (2011). Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China. *Atmospheric Chemistry and Physics*, 11(5), 2295–2308. <https://doi.org/10.5194/acp-11-2295-2011>

- Zhao, Y., Xia, Y., & Zhou, Y. (2018). Assessment of a high-resolution NOX emission inventory using satellite observations: A case study of southern Jiangsu, China. *Atmospheric Environment*, 190, 135–145. <https://doi.org/10.1016/j.atmosenv.2018.07.029>
- Zhou, T., Liu, H., Gou, P., & Xu, N. (2023). Conflict or Coordination? Measuring the relationships between urbanization and vegetation cover in China. *Ecological Indicators*, 147, 109993. <https://doi.org/10.1016/j.ecolind.2023.109993>
- Zhou, X., Li, M., Huang, X., Liu, T., Zhang, H., Qi, X., et al. (2025). Urban meteorology–chemistry coupling in compound heat–ozone extremes. *Nature Cities*, 2(9), 847–856. <https://doi.org/10.1038/s44284-025-00302-1>