Mitigating ozone damage to ecosystem productivity through sectoral and regional emission controls: a case study in the Yangtze River Delta, China

Yadong Lei, Xu Yue, Zhili Wang, Hong Liao, Lin Zhang, Chenguang Tian, Hao Zhou, Junting Zhong, Lifeng Guo, Huizheng Che and Xiaoye Zhang

1 State Key Laboratory of Severe Weather and Key Laboratory of Atmospheric Chemistry of CMA, Chinese Academy of Meteorological Sciences, Beijing 100081, People's Republic of China
2 Jiangsu Key Laboratory of Atmospheric Environment Monitoring and Pollution Control, Jiangsu Collaborative Innovation Center of Atmospheric Environment and Equipment Technology, School of Environmental Science and Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, People's Republic of China
3 Laboratory for Climate and Ocean–Atmosphere Studies, Department of Atmospheric and Oceanic Sciences, School of Physics, Peking University, Beijing 100871, People's Republic of China
4 Climate Change Research Center, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, People's Republic of China

* Author to whom any correspondence should be addressed.
E-mail: yuexu@nuist.edu.cn

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Abstract
The land ecosystems of China are estimated to provide an important sink for the increased atmospheric carbon dioxide (CO₂), but are undermined by severe ozone (O₃) pollution. Mitigation of O₃ damage to ecosystems remains a challenge considering that O₃ precursors are emitted from a wide range of anthropogenic sectors and O₃ formations are also affected by regional transport. Here, we combine chemical transport and dynamic vegetation models to quantify the benefits of sectoral and regional emission controls for the recovery of gross primary productivity (GPP) in the Yangtze River Delta (YRD). For sectoral emission controls, the largest mitigation of O₃ damage to GPP in YRD by 3.1 ± 0.4 and 2.2 ± 0.2 Gg[C] d⁻¹ with 50% reductions in the emissions from industry and transportation sectors, respectively. For regional emission controls, reducing 50% anthropogenic emissions outside YRD can mitigate GPP losses by 18.6 ± 3.5 Gg[C] d⁻¹, larger than the recovery of 10.1 ± 1.6 Gg[C] d⁻¹ by the 50% reductions of anthropogenic emissions within YRD. Moreover, summer months, especially July are the best period for GPP recovery from anthropogenic emission controls. Our results highlight the importance of sectoral and regional emission controls to mitigate O₃ damage to ecosystem productivities in YRD.

1. Introduction
Ozone (O₃) and haze episodes are two emerging and connected challenges in China (Li et al 2019, Ma et al 2021, Qu et al 2021, Zhao et al 2022). Since 2013, stringent air pollution control named 'Clean Air Actions' has been implemented by Chinese government to solve the air quality problem. Consequently, concentrations of particulate matter decreased substantially ever since (Fu et al 2019, Zhang et al 2019, He et al 2021). However, O₃ pollution is getting worse (Liu and Wang 2020, Lu et al 2020, Dang et al 2021), especially in Yangtze River Delta (YRD) where the ratio of O₃-dominated episodes increased from 13.9% in 2013 to 50.4% in 2017 (www.cnemc.cn/jchb/zgbhjkgb/). As a secondary gas pollutant, O₃ is produced by chemical reactions of nitrogen oxides (NOₓ) and volatile organic compounds (VOCs) in the presence of sunlight (Atkinson 2000, Chen and Brune 2012). In China, O₃ precursors such as NOₓ and VOCs are mainly emitted by anthropogenic sources, including industry, transportation, and power sectors (Lu et al 2019, Li et al 2020). Meanwhile, surface O₃ is likely to reach high levels on
hot and sunny days due to accelerated photochemical rates and reduced plant stomatal uptake (Gong and Liao 2019, Lin et al. 2020, Lei et al. 2022).

High O\(_3\) concentrations near surface can not only threaten human health (Chen et al. 2012, Lu et al. 2020), but also reduce terrestrial ecosystem productivity (Yue et al. 2017, Agathokleous et al. 2020, Unger et al. 2020, Lei et al. 2021). Open-top chambers and free-air experiments revealed visible O\(_3\) injuries on numerous plant species, including trees, shrubs, and herbs (Wan et al. 2014, Feng et al. 2015). Based on these measurements, some O\(_3\) vegetation damage schemes were developed, for example Sitch et al. (2007) and Lombardozzi et al. (2015), to predict reductions in photosynthesis using O\(_3\) stomatal uptake and empirical damaging sensitivities. Numerical models implementing these schemes showed that O\(_3\) causes strong damages to ecosystem productivity from regional to global scales (Zhou et al. 2018, Unger et al. 2020).

Ecosystem is an important carbon sink in China. Every year, terrestrial ecosystem uptakes \(\sim\)10% of the total anthropogenic carbon emissions in China (Piao et al. 2009, Fang et al. 2018). However, the land sink capacity in China is threatened by the worsening O\(_3\) pollution that induces losses of \(\sim\)15% in ecosystem productivity (Yue et al. 2017, Unger et al. 2020). Therefore, how to mitigate O\(_3\) damages on land ecosystem productivity is an urgent question. Here, we combine chemical transport and dynamic vegetation models to examine how much carbon loss can be avoided through sectoral and regional emission controls of O\(_3\) precursors. We focus specifically on the land ecosystems in YRD, where vegetation cover is high and O\(_3\) level was increasing fast in recent years. Emission controls include stringent 50% reductions in anthropogenic emissions from five sectors and different regions, a decreasing ratio likely achieved by the 2060s with the national carbon neutrality target (Tong et al. 2020, Lamboll et al. 2021, He et al. 2022). Surface O\(_3\) is predicted by the chemical transport model under different emission controls, and is then used to influence carbon cycle in the vegetation model.

2. Methods and materials

2.1. The GEOS-Chem chemical transport model
GEOS-Chem model is a widely used global 3D chemical transport model for simulating concentrations of gas-phase pollutants and aerosols with a detailed H\(_2\)O–NO\(_x\)–VOC–O\(_3\)–halogen–aerosol chemistry mechanism (Kim et al. 2015a, Lee et al. 2017, Lu et al. 2019, Porter and Heald 2019, Gong et al. 2021). This model uses Fast-JX scheme to compute photoysis rates (Bian and Prather 2002). Biogenic VOC (BVOC) emissions are computed based on the Model of Emissions of Gases and Aerosols from Nature (MEGAN v2.1) (Guenther et al. 2012). The dry deposition for gases is computed based on the resistance-in-series scheme (Wesely 1989). The global anthropogenic emission inventory is obtained from Community Emissions Data System (Ho et al. 2018). Anthropogenic emissions in China are computed based on Multi-resolution Emission Inventory (MEIC), which estimates SO\(_2\), NO\(_x\), CO, NMVOC, NH\(_3\), PM\(_{10}\), PM\(_{2.5}\), BC, OC, and CO\(_2\) emissions from five source sectors including agriculture (AGR), industry (IND), power (POW), residential (RES), and transportation (TRA) (Zheng et al. 2018). Notably, agriculture source sector only includes NH\(_3\) emissions. Total anthropogenic emissions from each sector in YRD are summarized in table S1 (available online at stacks.iop.org/ERL/17/065008/mmedia). In this study, nested GEOS-Chem version 12.0.0 with resolution of 0.5\(^\circ\) \(\times\) 0.625\(^\circ\) is driven by the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA2) meteorological fields to predict the changes of tropospheric O\(_3\) under different anthropogenic emission controls.

2.2. The Yale Interactive terrestrial Biosphere (YIBs) vegetation model
The YIBs model is a process-based vegetation model designed to simulate global carbon cycle with dynamical prediction of leaf area index (LAI) and tree height (Yue and Unger 2015). Leaf-level photosynthesis is computed using Farquhar et al. (1980) scheme. The leaf photosynthesis is further upscaled to canopy level by separating the responses of sunlit and shaded leaves to diffuse and direct radiation (Sprint 
Ty et al. 1986). Calculations of LAI and carbon allocation follow the Joint UK Land Environment Simulator (JULES) model (Clark et al. 2011). The Moderate Resolution Imaging Spectroradiometer (MODIS) land types and cover fractions are aggregated into eight plant functional types (figure S1), including evergreen needleleaf forest, deciduous broadleaf forest, evergreen broadleaf forest, shrubland, C\(_3\)/C\(_4\) grasses, and C\(_3\)/C\(_4\) crops to calculate carbon uptake in the YRD. The YIBs model applies Kim et al. (2015b) scheme to build phenology. For crops, the plant date and harvest date are fixed based on observations. For other plant functional types, leaf phenology is generally controlled by temperature, water availability, and photoperiod. The YIBs model has been comprehensively validated against site-level observations and satellite retrievals (Yue et al. 2015, 2017, Yue and Unger 2018). Since 2020, the YIBs model has joined the multi-model ensemble project ‘Trends in the land carbon cycle (TRENDY)’ to estimate global carbon budget (Friedlingstein et al. 2020). In this study, the YIBs model is driven by the same meteorological fields (MERRA2) as GEOS-Chem with a higher resolution of 0.25\(^\circ\) \(\times\) 0.3125\(^\circ\).

The semi-mechanistic O\(_3\) damage scheme is coupled into YIBs to quantify the carbon losses by
surface $O_3$ (Sitch et al 2007, Lei et al 2020, Unger et al 2020). The $O_3$-induced photosynthesis loss ($A'$, $\mu$mol m$^{-2}$s$^{-1}$) is calculated by multiplying the $O_3$ damage factor ($\alpha$) to the original leaf photosynthesis ($A$, $\mu$mol m$^{-2}$s$^{-1}$):

$$A' = A \times \alpha.$$  \hspace{1cm} (1)

The $\alpha$ is calculated based on excessive $O_3$ flux ($EF_{O_3}$, $\mu$mol m$^{-2}$s$^{-1}$) and sensitivity coefficient ($\beta$):

$$\alpha = EF_{O_3} \times \beta.$$ \hspace{1cm} (2)

The $\beta$ has two values for each vegetation type, representing low to high $O_3$-damaging sensitivities. The $EF_{O_3}$ is calculated based on stomatal $O_3$ flux ($F_{O_3}$, $\mu$mol m$^{-2}$s$^{-1}$) and $O_3$ damaging threshold ($T_{O_3}$, $\mu$mol m$^{-2}$s$^{-1}$):

$$EF_{O_3} = \max(F_{O_3} - T_{O_3}, 0).$$ \hspace{1cm} (3)

The $T_{O_3}$ represents the $O_3$ tolerance for each vegetation type. The $F_{O_3}$ is calculated based on surface $O_3$ concentrations ([O$_3$], $\mu$mol m$^{-3}$), aerodynamic resistance ($R_a$, s m$^{-1}$), boundary layer resistance ($R_b$, s m$^{-1}$), stomatal conductance ($R_s$, s m$^{-1}$), and the ratio of leaf resistance ($R_s$) to leaf resistance of water vapor ($k$):

$$F_{O_3} = [O_3]/(R_a + R_b + k \times R_s).$$ \hspace{1cm} (4)

The $O_3$-damaging gross primary productivity (GPP) is calculated by integrating $A'$ over all canopy layers:

$$GPP' = \int_0^{LAI} A' dL.$$ \hspace{1cm} (5)

This scheme has been well validated against hundreds of experimental data collected globally and in China (Yue et al 2017, Yue and Unger 2018).

### 2.3. Model simulations

In this study, we conduct ten GEOS-Chem runs and 20 YIBs runs to explore the changes of $O_3$-induced GPP reductions in the YRD by different anthropogenic emission control strategies (table 1). In the control run (CTRL), the GEOS-Chem model is forced with all sources of emissions. The SHUT run uses the same emissions as CTRL, except for shutting down anthropogenic emissions in China. In five sensitivity runs, the model is forced with all anthropogenic emissions but 50% emission reductions in YRD from a specific sector, including agriculture (AGR_RED50%), industry (IND_RED50%), power (POW_RED50%), residential source (RES_RED50%), or transportation (TRA_RED50%). We perform another three runs with GEOS-Chem to explore the impacts of collaborative emission reductions and regional transport on $O_3$ pollution, including 50% reductions of anthropogenic emissions outside YRD (YRD$_{out}$RED50%), inside YRD (YRD$_{in}$RED50%), or the whole anthropogenic emissions in China (CHN_RED50%). For above simulations, anthropogenic emissions of all pollution species are retained or perturbed with the same ratios (e.g. reduce by 50% or 100%). All runs are conducted from January to September in 2017 and the results of last 6 months are used to investigate the mitigation effects of anthropogenic emission controls on $O_3$-induced GPP losses during the growing season (April–September). The simulated hourly surface $O_3$ concentrations from each GEOS-Chem run are used to drive the YIBs model with either high or low sensitivities, making a total of 20 YIBs runs. The derived GPP losses with low and high $O_3$-damaging sensitivities are averaged for comparisons and one standard deviation of low and high $O_3$-damaging sensitivities represents uncertainties of $O_3$ damage on GPP.

### 2.4. Validation data

Ground-based hourly $O_3$ concentrations in 2017 growing-season are collected from the observational network of the China Ministry of Ecology and Environment (MEE) (http://datacenter.mee.gov.cn/). With quality control, continuous measurements at 157 sites in YRD are selected to evaluate the simulated surface $O_3$ from GEOS-Chem. We use the daily maximum 8 h average (MDA8) $O_3$ as the metric in validation. Benchmark GPP are obtained from the Global LAAnd Surface Satellite (GLASS) product generation system (Yuan et al 2010, Zhao et al 2013). The GLASS GPP agrees well with FLUXNET observations (Yu et al 2018) and has been widely used in the estimate of global and regional carbon budgets (Jiang et al 2021).

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**Table 1. Summary of simulations with GEOS-Chem models.**

| Name             | Emissions                                      |
|------------------|------------------------------------------------|
| CTRL             | All emissions                                  |
| SHUT             | Shut down anthropogenic emissions in China     |
| AGR_RED50%       | Reduce agriculture emissions alone             |
| IND_RED50%       | Reduce industry emissions alone by 50% in YRD  |
| POW_RED50%       | Reduce power emissions alone by 50% in YRD     |
| RES_RED50%       | Reduce residential emissions alone by 50% in YRD|
| TRA_RED50%       | Reduce transportation emissions alone by 50% in YRD|
| YRD$_{out}$RED50%| Reduce anthropogenic emissions by 50% outside YRD|
| YRD$_{in}$RED50% | Reduce anthropogenic emissions by 50% in YRD   |
| CHN_RED50%       | Reduce anthropogenic emissions by 50% in China  |
3. Results

3.1. Model validations

Simulated mean surface O₃ concentrations and GPP during the growing season in 2017 are validated using site-level measurements from MEE and benchmark GPP from GLASS (figure 1). We choose 2017 here as the regional MEIC inventory used in GEOS-Chem is only updated to 2017 (http://meicmodel.org/). Observed O₃ shows high values in the north and east of YRD (figure 1(a)), following the large regional emissions (figure S2). Compared to observations, the GEOS-Chem model well captures the spatiotemporal variation of surface O₃, with a high correlation coefficient of 0.6 ($p < 0.01$) and a low normalized mean bias of 4% for 28725 statistical samples (figures 1(b) and (c)). Similarly, the YIBs model reasonably depicts the spatial distribution of GPP with an increasing gradient from the north to the south of YRD (figures 1(d) and (e)). The correlation coefficient is 0.7 ($p < 0.01$) and the normalized mean bias is only 10% for 467 statistical samples between observations and simulations (figure 1(f)). The limited biases in both the simulated O₃ and GPP consolidate our strategies in quantifying the changes of O₃-induced carbon losses under different emission controls using the GEOS-Chem and YIBs models.

3.2. O₃ damage to ecosystem productivity

Ecosystem productivity in YRD is threatened by the severe O₃ pollution (figure 2). In 2017, surface O₃ reduces regional GPP by 184.1 ± 44.5 Gg[C] d⁻¹ during the growing season in YRD (figure 2(a)), accounting for a fraction of 10% to the total GPP. Regional maximum reductions are distributed in Zhejiang province and southern Anhui province, although the high surface O₃ concentrations are predicted in the northern Anhui province and southern Jiangsu province. Such discrepancy is likely because that northern Anhui province and southern Jiangsu province is mainly covered by crops which have a higher O₃ damage critical threshold than other ecosystem types (Unger et al 2020). In the growing season, O₃-induced GPP reductions reach maximums in summer (June–August) due to large GPP and high surface O₃ concentrations (figure 2(c)). With sensitivity simulation SHUT, we quantify the effects of anthropogenic emissions on...
ecosystem productivity in YRD. It is found that shutting down all anthropogenic emissions in China decreases regional mean O$_3$ by 29.2 ppbv during the growing season in YRD (figure S3(a)). Consequently, O$_3$-induced GPP loss is alleviated by 144.9 ± 31.5 Gg[C] d$^{-1}$ in YRD (figure 2(b)). The largest benefit of GPP recovery occurs in July in response to the largest O$_3$ reduction by shutting down all anthropogenic emissions (figures 2(c) and S3(b)). Although anthropogenic emissions contribute only 45% to the total surface O$_3$, shutting down anthropogenic emissions helps mitigate 79% of total O$_3$-induced ∆GPP during the growing season in YRD. Therefore, exploring the effects of anthropogenic emission controls on O$_3$-induced ∆GPP is of great value for ecosystem health in YRD.

3.3. Changes of surface O$_3$ by sectoral and regional emission controls
Simulated surface O$_3$ in YRD is influenced by different anthropogenic emission control strategies (figure 3). For 50% anthropogenic emission reductions in industrial and transportation sectors, regional mean surface O$_3$ in YRD decreases by 0.6 and 0.4 ppb during the growing season, respectively (figures 3(b) and (e)). In contrast, regional mean surface O$_3$ increases by 1.0 ppb during the growing season with 50% reductions in agriculture emissions (figure 3(a)). For this specific sector, emissions are mainly in the form of ammonia, the reduction of which does not affect O$_3$ precursors but decrease ammonium and PM$_{2.5}$ concentrations (figure S4). Consequently, the reductions of aerosols reduce the uptake of HO$_2$ and results in more production of surface O$_3$ (Li et al 2019). As a comparison, reductions of anthropogenic emissions in other sectors such as power and residential have smaller impacts on surface O$_3$ with regional mean changes of 0.2 and 0.1 ppb, respectively (figures 3(c) and (d)).

Compared to emission controls of a single sector, collaborative emission reductions have better effects in the mitigation of O$_3$ pollution. For 50% emission reductions in all sectors within YRD, regional mean surface O$_3$ shows a large reduction of −2.0 ppb during the growing season (figure 3(f)), which has better mitigation effects than the sum of independent emission reductions of five sectors (figures 3(a)–(e)). This is because that there are inhomogeneous emissions for O$_3$ precursors, such as NOx and VOCs from different sectors. For example, power sector accounts for 20% of total NOx emissions but only <1% of total VOCs emissions. Thus, anthropogenic
emission control from power sector means only NOx emissions reductions, which will increase surface O3 in YRD. Regionally, the largest surface O3 reduction of −7.0 ppb is found in central Zhejiang province. However, an increase of surface O3 up to 6.0 ppb is predicted in the south of Jiangsu province when regional anthropogenic emissions are reduced by 50% (figure 3(f)). This is because southern Jiangsu is considered as a VOC-limited regime due to low HCHO/NO2 ratios (Wang and Liao 2020, Li et al 2021, Xu et al 2021). The O3 concentrations in the region would be elevated with the reduced NOx emissions alone or the same proportional reduction of VOCs and NOx emissions (Yang et al 2021). Such phenomenon that O3 increases with the reduction of VOCs and NOx emissions in YRD is also observed during the 2019 novel coronavirus pandemic, which provides a natural experiment to assess the effects of precursor changes on surface O3 (Wang et al 2021, Zhu et al 2021).
Figure 4. Simulated growing-season mean changes in O$_3$-induced GPP reductions (units: g[C] m$^{-2}$ d$^{-1}$) by different emission controls. O$_3$-induced GPP changes are caused by 50% reductions in anthropogenic emissions from agriculture (a), industry (b), power (c), residential (d), and transportation (e) sources, respectively. Panels (f)–(h) represent O$_3$-induced GPP changes due to reducing 50% anthropogenic emissions inside YRD, outside YRD, and over all China, respectively. The regional GPP changes caused by changes in O$_3$ are shown on each panel. Panel (i) represents seasonal cycle of regional GPP recovery (units: g[C] d$^{-1}$) during the growing season in YRD by sectoral and/or regional anthropogenic emission controls. The error bars represent low to high O$_3$-damaging sensitivities.

Similar to local emission control, the 50% reductions of anthropogenic emissions outside YRD results in a reduction of $-1.9$ ppb in regional mean O$_3$ concentrations (figure 3(g)). Such change is most significant in the western YRD with O$_3$ reductions exceeding $-5.0$ ppb. The magnitude of O$_3$ reduction decreases gradually from the west to east, suggesting that regional transport of O$_3$ and its precursors to YRD is mainly from inland areas. As a comparison, reducing 50% anthropogenic emissions over China results in a considerable reduction of $-4.7$ ppb in regional mean surface O$_3$ over YRD (figure 3(h)), with a spatial pattern merging the O$_3$ changes by 50% reductions of emissions inside (figure 3(f)) and outside (figure 3(g)) YRD.

We further investigate the seasonal variations in O$_3$ changes by different anthropogenic emission controls during the growing season in YRD (figure 3(i)). The results show that O$_3$ reductions driven by regional anthropogenic emission controls,
including YRD\textsubscript{out} RED50\%, YRD\textsubscript{in} RED50\%, and CHN\textsubscript{RED50\%} exhibit similar seasonal variations, increasing from April to July and then decreasing. However, there are inconsistent seasonal variations of O\textsubscript{3} changes driven by sectoral anthropogenic emission controls. The O\textsubscript{3} changes reach a maximum in July for 50\% anthropogenic emission reductions in power, transportation, and residential sectors, but in June for 50\% anthropogenic emission reductions in agriculture and industry.

### 3.4. Mitigation of O\textsubscript{3} damages to ecosystem productivity

Emission controls bring benefits to the recovery of ecosystem productivity during the growing season in YRD (figure 4). O\textsubscript{3}-induced regional ΔGPP is mitigated by 3.1 ± 0.4 Gg[C] d\textsuperscript{-1} with 50\% emission reductions from industry sector (figure 4(b)) and 2.2 ± 0.2 Gg[C] d\textsuperscript{-1} with 50\% emission reductions from transportation sector (figure 4(e)). However, 50\% emission reductions from agriculture, power, and residential sectors result in additional carbon losses of 5.2 ± 0.9, 0.1 ± 0.1, and 1.4 ± 0.3 Gg[C] d\textsuperscript{-1}, respectively (figures 4(a), (c) and (d)) due to enhanced regional surface O\textsubscript{3}. The sum of regional ΔGPP is −1.5 ± 0.8 Gg[C] d\textsuperscript{-1} from the individual emission controls at the five sectors during the growing season in YRD.

We further explore the impacts of regional and sectoral collaborative emission controls on ecosystem productivity during the growing season in YRD. With the YRD\textsubscript{in} RED50\% simulation, the O\textsubscript{3}-induced regional ΔGPP is mitigated by 10.1 ± 1.6 Gg[C] d\textsuperscript{-1} (figure 4(f)), which is much larger than sum of independent emission reduction in five sectors. Such difference illustrates that collaborative emission reductions in all sectors have larger benefits for the recovery of ecosystem productivity. Although there is smaller surface O\textsubscript{3} reduction from YRD\textsubscript{out} RED50\% than YRD\textsubscript{in} RED50\% simulations, a larger regional GPP recovery of 18.6 ± 3.5 Gg[C] d\textsuperscript{-1} is achieved in the former experiment (figure 4(f)). This is because surface O\textsubscript{3} reductions from YRD\textsubscript{out} RED50\% simulation is mainly located in southwestern YRD (figure 3(f)), where the largest GPP is predicted (figure 1(c)). The largest benefit of ecosystem productivity is simulated by reducing 50\% anthropogenic emissions in China, which mitigates O\textsubscript{3}-induced ΔGPP by 33.3 ± 6.1 Gg[C] d\textsuperscript{-1} in YRD (figure 4(h)).

The seasonal variations in GPP recovery from sectoral and regional anthropogenic emission controls follow those in O\textsubscript{3} changes (figure 4(i)). For regional anthropogenic emission controls, the O\textsubscript{3}-induced GPP losses are mitigated by 43.2 ± 7.2, 19.8 ± 3.1, and 72.2 ± 12.1 Gg[C] d\textsuperscript{-1} in July for YRD\textsubscript{out} RED50\%, YRD\textsubscript{in} RED50\%, and CHN\textsubscript{RED50\%} simulations, respectively. These numbers account for 39\%, 33\%, and 36\% of total GPP recovery during the growing season in YRD. For sectoral anthropogenic emission controls, the maximum GPP recovery of 6.3 ± 0.8 Gg[C] d\textsuperscript{-1} occurs in June for IND\textsubscript{RED50\%} simulation, but 4.7 ± 0.5 Gg[C] d\textsuperscript{-1} in July for TRA\textsubscript{RED50\%} simulation. These results indicate that summer months, especially July are the best period for GPP recovery from anthropogenic emission controls.

### 4. Conclusion and discussion

The land ecosystems of China are undermined by severe O\textsubscript{3} pollution in recent years. In this study, we combined GEOS-Chem and YIBs models to assess the benefits to ecosystem productivities from sectoral and regional emission controls during the growing season in YRD. For sectoral emission controls, industry and transportation have larger contributions to the recovery of O\textsubscript{3}-induced GPP damages than power and residential sectors. Reducing 50\% emissions from industry and transportation sectors decrease regional mean surface O\textsubscript{3} by 0.6 and 0.4 ppbv, which can mitigate O\textsubscript{3}-induced GPP losses of 3.1 ± 0.4 and 2.2 ± 0.2 Gg[C] d\textsuperscript{-1} during the growing season in YRD, respectively. For regional pollution controls, the reduction of 50\% anthropogenic emissions outside YRD can mitigate a GPP loss of 18.6 ± 3.5 Gg[C] d\textsuperscript{-1} during the growing season in YRD, which is higher than the 10.1 ± 1.6 Gg[C] d\textsuperscript{-1} mitigated by a reduction of 50\% in local anthropogenic emissions alone. In addition, anthropogenic emission controls in summer months, especially July can bring larger benefits of GPP recovery than the rest period of the growing season.

The predicted O\textsubscript{3} reductions in YRD by shutting down all anthropogenic emission in China are comparable to previous studies (Wang et al 2011, Lu et al 2019). Our simulated GPP recoveries from independent sectoral emission controls are in general consistent with simulations by Unger et al (2020), except that the latter predicted a positive contribution by agriculture emission reductions to mitigating O\textsubscript{3}-induced carbon losses while we predicted an opposite contribution with negative effects. In the GAINS inventory used in Unger et al (2020), agriculture sector includes NO\textsubscript{x}, CH\textsubscript{4} and NH\textsubscript{3} gases, which affect O\textsubscript{3} production substantially. However, the agriculture sector in the MEIC inventory used in this study includes only NH\textsubscript{3}, leading to increases of surface O\textsubscript{3} following the decreased ammonium and PM\textsubscript{2.5}. In addition, compared with global assessment by Unger et al (2020), our regional assessment reveals some new insights for the benefits of GPP recovery from anthropogenic emission controls: (a) the responses of GPP recovery show large spatial heterogeneity. The 50\% reduction
of emissions from industry and transportation sectors results in a general recovery of O$_3$-induced GPP reductions in YRD, but with regional degradation in eastern Jiangsu province, which is defined as a VOC-limited regime. (b) Compared to emission controls of a single sector, collaborative emission reductions in all sectors have larger benefits for the recovery of O$_3$-induced GPP losses. With 50% emission reductions in all sectors in YRD, the O$_3$-induced regional ΔGPP is mitigated by 10.1 ± 1.6 Gg[C] d$^{-1}$, which is much larger than sum of independent emission reduction in five sectors. (c) Anthropogenic emission control outside the region is also an effective way to mitigate local O$_3$-induced GPP losses. The GPP recovery by a 50% emission cut outside YRD is about twice that by a 50% emission cut inside YRD. This is because the regional GPP recovery is dependent on both O$_3$ changes and the forest coverage. (d) The efficiencies of anthropogenic emission controls on GPP recovery vary through the growing season. Summer, especially July is the best period for recovery of O$_3$-induced GPP losses by anthropogenic emission controls. (e) The net effect of emission control on GPP recovery is nonlinear. The 50% reduction of all emissions results in a GPP recovery of 33.3 ± 6.1 Gg[C] d$^{-1}$ in YRD, accounting for only 18% of the total regional GPP losses (figure 2(a)). As a comparison, the 100% reduction of all anthropogenic emissions leads to a GPP recovery of 144.9 ± 31.5 Gg[C] d$^{-1}$, which is up to 79% of the total GPP loss. Such nonlinearity suggests that only the deep cut of anthropogenic emissions (e.g. >50%) can bring effective benefits to the ecosystem carbon assimilation.

Our study revealed large benefits of recovering ecosystem functions associated with the pollution reduction towards carbon neutrality. Currently, reductions of emissions from industry and transportation sectors brings the largest benefits to the recovery of carbon uptake by land ecosystems in YRD. Such benefits will be much stronger with simultaneous emission controls of multiple sectors and regions than a single sector or from local areas. These gains in carbon sequestration, though likely vary from cities to metropolitans, should be considered to in part offset the large costs in the air pollution regulation. In our current estimate, we applied a constant 50% reduction rate for all emission sectors. However, the cost of emission control varies among sectors and regions, leading to varied reduction percentages for O$_3$ precursors in reality. Therefore, scientific pathways of emission reduction are required and the associated GPP recovery need further investigations.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no competing interests.

ORCID iDs

Xu Yue https://orcid.org/0000-0002-8861-8192
Zhili Wang https://orcid.org/0000-0002-4392-3230
Lin Zhang https://orcid.org/0000-0003-2383-8431

References

Agathokleous E et al 2020 Ozone affects plant, insect, and soil microbial communities: a threat to terrestrial ecosystems and biodiversity Sci. Adv. 6 eabc1176
Atkinson R 2000 Atmospheric chemistry of VOCs and NO$_x$ Atmos. Environ. 34 2063–101
Bian H S and Prather M J 2002 Fast-J2: accurate simulation of stratospheric photolysis in global chemical models J. Atmos. Chem. 41 281–96
Chen C, Zhao B and Weschler C J 2012 Assessing the influence of indoor exposure to ‘outdoor ozone’ on the relationship between ozone and short-term mortality in US communities Environ. Health Perspect. 120 235–40
Chen S and Brune W H 2012 Global sensitivity analysis of ozone production and O$_3$-NO$_x$-VOC limitation based on field data Atmos. Environ. 55 288–96
Clark D B et al 2011 The Joint UK Land Environment Simulator (JULES), model description—part 2: carbon fluxes and vegetation dynamics Geosci. Model. Dev. 4 701–22
Dang R J, Liao H and Fu Y 2021 Quantifying the anthropogenic and meteorological influences on summertime surface ozone in China over 2012–2017 Sci. Total Environ. 754 142394
Fang J Y, Yu G R, Liu L L, Hu S J and Chapin F S 2018 Climate change, human impacts, and carbon sequestration in China introduction Proc. Natl. Acad. Sci. USA 115 4015–20
Farquhar G D, Caemmerer S V and Berry J A 1980 A biochemical model of photosynthetic CO$_2$ assimilation in leaves of C$_3$ species Planta 149 78–90
Feng Z Z, Hu E Z, Wang X K, Jiang L J and Liu X J 2015 Ground-level O$_3$ pollution and its impacts on food crops in China: a review Environ. Pollut. 199 42–48
Friedlingstein P et al 2020 Global carbon budget 2020 Earth Syst. Sci. Data 12 3269–340
Fu Y, Liao H and Yang Y 2019 Interannual and decadal changes in tropospheric ozone in China and the associated chemistry-climate interactions: a review Adv. Atmos. Sci. 36 975–93
Gong C and Liao H 2019 A typical weather pattern for ozone pollution events in North China Atmos. Chem. Phys. 19 13725–40
Gong C, Liao H, Yue X, Ma Y M and Lei Y D 2021 Impacts of ozone-vegetation interactions on ozone pollution episodes in North China and the Yangtze River Delta Geophys. Res. Lett. 48 e2021GL093814
Guenther A B, Jiab J, Xae H, C L, Sakuliyantaittaya T, Duhl T, Emmons L K and Wang X 2012 The Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1): an extended and updated framework for modeling biogenic emissions Geosci. Model. Dev. 5 1471–92
He J et al 2022 Towards carbon neutrality: a study on China’s long-term low-carbon transition pathways and strategies *Environ. Sci. Technol. 9* 100134

He Q Q, Zhang M, Song Y M and Huang B 2021 Spatiotemporal assessment of PM$_{2.5}$ concentrations and exposure in China from 2013 to 2017 using satellite-derived data *J. Clean. Prod.* 286 124963

Hoeyls R M et al 2018 Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data System (CEDS) *Geosci. Model. Dev.* 11 369–408

Jiang W X, Wang L C, Zhang M, Yao R, Chen X X, Gui X, Sun J and Cao Q 2021 Analysis of drought events and their impacts on vegetation productivity based on the integrated surface drought index in the Hanjiang River Basin, China *Atmos. Res.* 254 105536

Kim P S et al 2015a Sources, seasonality, and trends of southeast US aerosol: an integrated analysis of surface, aircraft, and satellite observations with the GEOS-Chem chemical transport model *Atmos. Chem. Phys.* 15 10411–33

Kim Y, Moorcroft P R, Aineov I, Puma M J and Kiang N Y 2015b Variability of phenology and fluxes of water and carbon with observed and simulated soil moisture in the Ent Terrestrial Biosphere Model (Ent TBM version 1.0.1.0.0) *Geosci. Model. Dev.* 8 3837–65

Lamboll B D, Jones C D, Skeie R B, Fiedler S, Samset B H, Gillett N P, Rogelj J and Forster P M 2021 Modifying emissions scenario projections to account for the effects of COVID-19: protocol for CovidMIP *Geosci. Model. Dev.* 14 3683–95

Lee H M, Park R J, Henze D K, Lee S, Shim C, Shin H J, Moon K J et al 2022 Towards carbon neutrality: a study on China’s carbon balance of terrestrial ecosystems in China *Nature* 548 1099–U82

Porter W C and Head I C 2019 The mechanisms and meteorological drivers of the summertime ozone-temperature relationship *Atmos. Chem. Phys.* 19 133567–81

Qu Y W, Voulgarakis A, Wang T J, Kasar M, Wells C, Yuan C, Varma S and Mansfield L 2021 A study of the effect of aerosols on surface ozone through meteorology feedbacks over China *Atmos. Chem. Phys.* 21 5705–18

Sitch S, Cox P M, Collins W J and Huntingford C 2007 Indirect radiative forcing of climate change through ozone effects on the land-carbon sink *Nature* 448 791–U4

Spituc C 1986 Separating the diffuse and direct component of global radiation and its implications for modeling canopy photosynthesis part II—calculation of photosynthesis *Agric. For. Meteorol.* 38 331–42

Tong D et al 2020 Dynamic projection of anthropogenic emissions in China: methodology and 2015–2050 emission pathways under a range of socio-economic, climate policy, and pollution control scenarios *Atmos. Chem. Phys.* 20 5729–57

Unger N, Zheng Y Q, Yue X and Harper K L 2020 Mitigation of ozone damage to the world’s land ecosystems by source sector *Nat. Clim. Change* 10 134–7

Wan W X, Manning W J, Wang X K, Zhang H X, Sun X and Zhang Q Q 2014 Ozone and ozone injury on plants in and around Beijing, China *Environ. Pollut.* 191 215–22

Wang Y and Liao H 2020 Effect of emission control measures on ozone concentrations in Hangzhou during G20 meeting in 2016 *Chemosphere* 261 127729

Wang Y, Zhang Y, Hao J and Luo M 2011 Seasonal and spatial variability of surface ozone over China: contributions from background and domestic pollution *Atmos. Chem. Phys.* 11 3511–25

Wang Y, Zhu S Q, Ma J L, Shen J Y, Wang P F, Wang P and Zhang H L 2021 Enhanced atmospheric oxidation capacity and associated ozone increases during COVID-19 lockdown in the Yangtze River Delta *Sci. Total Environ.* 768 144796

Wesely M L 1989 Parameterization of surface resistances to gaseous dry deposition in regional-scale numerical-models *Atmos. Chem. Phys.* 23 1293–304

Xu J W, Huang X, Wang N, Li Y Y and Ding A J 2021 Understanding ozone pollution in the Yangtze River Delta of eastern China from the perspective of diurnal cycles *Sci. Total Environ.* 752 141928

Yang Y, Zhao G, Zhang L, Zhang J H, Yang X, Zhao X F, Zhang Y, Xi M X and Lu Y J 2021 Improvement of the satellite-derived NO$_2$ emissions on air quality modeling and its effect on ozone and secondary inorganic aerosol formation in the Yangtze River Delta, China *Atmos. Chem. Phys.* 21 5705–18

Yi T, Sun R, Xiao Z Q, Zhang Q, Liu G, Cui T X and Wang J M 2018 Estimation of global vegetation productivity from Global LAnd Surface Satellite data *Remote Sens.* 10 327

Yuan W P et al 2010 Global estimates of evapotranspiration and gross primary production based on MODIS and global water cycles data *Remote Sens. Environ.* 114 1416–33

Yue X and Unger N 2015 The Yale Interactive Terrestrial Biosphere model version 1.0: description, evaluation and implementation into NASA GISS ModelE2 *Geosci. Model. Dev.* 8 2399–417

Yue X and Unger N 2018 Fire air pollution reduces global ozone and resulting health impact in China since 2013 *Environ. Sci. Technol. Lett.* 7 240–7

Ma X D, Huang J P, Zhao T L, Liu C, Zhao K H, Xing J and Xiao W 2021 Rapid increase in surface ozone over the North China Plain during 2013–2019: a side effect of particulate matter reduction control? *Atmos. Chem. Phys.* 21 1–16

Piao S L, Fang J Y, Ciais P, Pfeil P, Huang Y, Sitch S and Wang T 2009 The carbon balance of terrestrial ecosystems in China *Nature* 458 1099–U82

Porter W C and Head C L 2019 The mechanisms and meteorological drivers of the summertime ozone-temperature relationship *Atmos. Chem. Phys.* 19 133567–81

Qu Y W, Voulgarakis A, Wang T J, Kasar M, Wells C, Yuan C, Varma S and Mansfield L 2021 A study of the effect of aerosols on surface ozone through meteorology feedbacks over China *Atmos. Chem. Phys.* 21 5705–18

Sitch S, Cox P M, Collins W J and Huntingford C 2007 Indirect radiative forcing of climate change through ozone effects on the land-carbon sink *Nature* 448 791–U4

Spituc C 1986 Separating the diffuse and direct component of global radiation and its implications for modeling canopy photosynthesis part II—calculation of photosynthesis *Agric. For. Meteorol.* 38 331–42

Tong D et al 2020 Dynamic projection of anthropogenic emissions in China: methodology and 2015–2050 emission pathways under a range of socio-economic, climate policy, and pollution control scenarios *Atmos. Chem. Phys.* 20 5729–57

Unger N, Zheng Y Q, Yue X and Harper K L 2020 Mitigation of ozone damage to the world’s land ecosystems by source sector *Nat. Clim. Change* 10 134–7

Wan W X, Manning W J, Wang X K, Zhang H X, Sun X and Zhang Q Q 2014 Ozone and ozone injury on plants in and around Beijing, China *Environ. Pollut.* 191 215–22

Wang Y and Liao H 2020 Effect of emission control measures on ozone concentrations in Hangzhou during G20 meeting in 2016 *Chemosphere* 261 127729

Wang Y, Zhang Y, Hao J and Luo M 2011 Seasonal and spatial variability of surface ozone over China: contributions from background and domestic pollution *Atmos. Chem. Phys.* 11 3511–25

Wang Y, Zhu S Q, Ma J L, Shen J Y, Wang P F, Wang P and Zhang H L 2021 Enhanced atmospheric oxidation capacity and associated ozone increases during COVID-19 lockdown in the Yangtze River Delta *Sci. Total Environ.* 768 144796

Wesely M L 1989 Parameterization of surface resistances to gaseous dry deposition in regional-scale numerical-models *Atmos. Chem. Phys.* 23 1293–304

Xu J W, Huang X, Wang N, Li Y Y and Ding A J 2021 Understanding ozone pollution in the Yangtze River Delta of eastern China from the perspective of diurnal cycles *Sci. Total Environ.* 752 141928

Yang Y, Zhao G, Zhang L, Zhang J H, Yang X, Zhao X F, Zhang Y, Xi M X and Lu Y J 2021 Improvement of the satellite-derived NO$_2$ emissions on air quality modeling and its effect on ozone and secondary inorganic aerosol formation in the Yangtze River Delta, China *Atmos. Chem. Phys.* 21 5705–18

Yu T, Sun R, Xiao Z Q, Zhang Q, Liu G, Cui T X and Wang J M 2018 Estimation of global vegetation productivity from Global LAnd Surface Satellite data *Remote Sens.* 10 327

Yuan W P et al 2010 Global estimates of evapotranspiration and gross primary production based on MODIS and global water cycles data *Remote Sens. Environ.* 114 1416–33

Yue X and Unger N 2015 The Yale Interactive Terrestrial Biosphere model version 1.0: description, evaluation and implementation into NASA GISS ModelE2 *Geosci. Model. Dev.* 8 2399–417

Yue X and Unger N 2018 Fire air pollution reduces global terrestrial productivity *Nat. Commun.* 9 5413
Yue X, Unger N, Harper K, Xia X G, Liao H, Zhu T, Xiao J F, Feng Z Z and Li J 2017 Ozone and haze pollution weakens net primary productivity in China Atmos. Chem. Phys. 17 6073–89
Yue X, Unger N and Zheng Y 2015 Distinguishing the drivers of trends in land carbon fluxes and plant volatile emissions over the past 3 decades Atmos. Chem. Phys. 15 11931–48
Zhang Q et al 2019 Drivers of improved PM$_{2.5}$ air quality in China from 2013 to 2017 Proc. Natl Acad. Sci. USA 116 24463–9
Zhao K H et al 2022 Understanding the underlying mechanisms governing the linkage between atmospheric oxidative capacity and ozone precursor sensitivity in the Yangtze River Delta, China: a multi-tool ensemble analysis Environ. Int. 160 107060
Zhao X et al 2013 The Global LAnd Surface Satellite (GLASS) remote sensing data processing system and products Remote Sens. 5 2436–50
Zheng B et al 2018 Trends in China’s anthropogenic emissions since 2010 as the consequence of clean air actions Atmos. Chem. Phys. 18 14095–111
Zhou S S, Tai A P K, Sun S H, Sadiq M, Heald C L and Geddes J A 2018 Coupling between surface ozone and leaf area index in a chemical transport model: strength of feedback and implications for ozone air quality and vegetation health Atmos. Chem. Phys. 18 14133–48
Zhu S Q, Poetzscher J, Shen J Y, Wang S Y, Wang P and Zhang H L 2021 Comprehensive insights into O$_3$ changes during the COVID–19 from O$_3$ formation regime and atmospheric oxidation capacity Geophys. Res. Lett. 48 e2021GL093668