



1 **Climate-mediated surface ozone responses to** 2 **simultaneous multi-regional marine cloud brightening**

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16 **Abstract.** Marine cloud brightening (MCB) has been proposed as a regional solar radiation modification
17 strategy, yet its effects on atmospheric composition remain poorly understood. Here, using the
18 Community Earth System Model version 1 (CESM1), we isolate the climate-mediated response of
19 surface ozone (O₃) with a three-stage experimental design. We first determine a sea salt injection rate of
20 11.4 Tg yr⁻¹ in each of six oceanic regions, which is sufficient to offset the 1.0 W m⁻² effective radiative
21 forcing difference between SSP5-8.5 and SSP2-4.5 in 2050. We then simulate the coupled climate
22 response and prescribe the resulting sea surface temperature and sea ice fields in atmospheric chemistry
23 experiments without additional sea salt injection. The MCB injection decreases global annual mean sea
24 surface temperature by 0.44 °C and increases Arctic sea ice concentration by 9.7%. The resulting changes
25 in temperature, moisture, radiation, boundary-layer mixing, and transport produce spatially
26 heterogeneous surface O₃ responses. After a machine learning bias correction, boreal summer surface O₃
27 concentration decreases by 0.33 µg m⁻³ over China, remains nearly unchanged over Europe at +0.01 µg
28 m⁻³, and increases by 0.12 µg m⁻³ over the United States. The subregional responses are more
29 pronounced with decreases of 0.59 and 0.64 µg m⁻³ over western and eastern China and contrasting
30 changes of -0.19 and +0.14 µg m⁻³ over western and eastern Europe. A comprehensive evaluation of



31 MCB should therefore consider its consequences for regional air quality alongside its intended climate
32 effects.

33 **1 Introduction**

34 Surface ozone (O_3) is both an important air pollutant and a key trace gas with consequences for human
35 health, ecosystems, and climate. Its future evolution depends on both precursor emissions and climate
36 change. Even when precursor emissions are held fixed, climate change alone can alter surface O_3 through
37 changes in temperature, water vapor, boundary-layer structure, convection, and large-scale circulation
38 (Jacob & Winner, 2009; Schnell et al., 2016). O_3 sensitivity to precursor emissions may also shift across
39 socioeconomic pathways and chemical regimes, further coupling climate and atmospheric chemistry (Liu
40 et al., 2022). Tropospheric O_3 has increased substantially since the preindustrial era and is projected to
41 remain elevated in many regions through the twenty-first century (Gaudel et al., 2018; Griffiths et al.,
42 2021).

43 Rising greenhouse gas concentrations and declining anthropogenic aerosols are expected to sustain
44 warming during the twenty-first century, even under strong mitigation pathways (IPCC, 2021; Zhu et al.,
45 2026; Wang et al., 2023; Yang et al., 2023). Given the increasing risks associated with climate change
46 and the challenges of achieving rapid carbon emission reductions, solar radiation modification (SRM)
47 has been proposed as a potential mitigation approach to temporarily limiting global warming (Crutzen,
48 2006; IPCC, 2023). Marine cloud brightening (MCB) is a proposed SRM technique that seeks to enhance
49 the reflectivity of low marine clouds by injecting sea salt aerosols into the marine boundary layer (Yu et
50 al., 2026). The effectiveness of MCB relies primarily on aerosol-cloud interactions. Increased aerosol
51 concentrations act as additional cloud condensation nuclei, increasing cloud droplet number
52 concentrations while reducing droplet size. For a given liquid water path, these changes increase cloud
53 optical depth and albedo (Twomey, 1974). Smaller droplets may suppress precipitation, prolong cloud
54 lifetime, and increase cloud cover (Albrecht, 1989). The resulting cloud adjustments alter shortwave
55 radiation and can cool the climate system, although responses in cloud water, precipitation, and cloud
56 fraction may be nonlinear (Glassmeier et al., 2021; Chen et al., 2022; Chun et al., 2023).



57 Through coupled ocean–atmosphere feedbacks, MCB can modify sea surface temperature, sea ice,
58 precipitation, and atmospheric circulation well beyond the injection regions (Ahlm et al., 2017; Stjern et
59 al., 2018; Gabriel et al., 2017; Haywood et al., 2023). These responses may limit warming but can also
60 produce regional drying, drought risk, and circulation shifts (Zhang et al., 2023). Most MCB studies have
61 focused on physical climate variables, whereas consequences for atmospheric composition remain less
62 studied (Horowitz et al., 2020; Feingold et al., 2024). Surface O_3 is especially relevant because its
63 production, loss, and transport respond strongly to temperature, humidity, cloud cover, boundary-layer
64 dynamics, and circulation, all of which may change under MCB injection scenarios.

65 MCB can affect surface O_3 through direct chemical and climate-mediated pathways. In the direct
66 pathway, injected sea salt aerosol (SSA) can activate chlorine and bromine chemistry that destroys
67 tropospheric O_3 (Horowitz et al., 2020). Sea salt surfaces can also promote heterogeneous N_2O_5
68 hydrolysis, reduce NO_x recycling, and suppress O_3 production (Brown & Stutz, 2012; Jacob, 2000).
69 Uptake of HO_2 can weaken radical recycling, while aerosol-induced changes in actinic flux can alter
70 photolysis and the O_3 production and loss balance (Thornton et al., 2008; Martin et al., 2003). Because
71 MCB injection occurs over ocean, the influence of these processes on continental O_3 depends on
72 chemical lifetime and atmospheric transport.

73 The climate-mediated pathway operates through MCB-induced changes in sea surface temperature, sea
74 ice, boundary-layer thermodynamics, clouds, and large-scale circulation. These changes modify the
75 environment, in which HO_x – NO_x –VOC chemistry occurs and can alter O_3 production, loss, and transport.
76 MCB-induced circulation changes have already been shown to affect stratospheric O_3 , with responses
77 that vary by latitude and season (Bednarz et al., 2025). The corresponding response of surface O_3 ,
78 however, has not been quantified systematically.

79 Here we quantify the climate-mediated surface O_3 response to a simultaneous global MCB deployment
80 across six oceanic regions. The deployment is designed to reduce the 2050 effective radiative forcing
81 under SSP5-8.5 to the SSP2-4.5 level. We first simulate the coupled climate response and then use the
82 resulting sea surface temperature (SST) and sea ice concentration (SIC) to drive atmospheric chemistry
83 experiments, with particular attention to regional contrasts over China, Europe, and the United States.

84



85 **2 Methods**

86 **2.1 Model description**

87 We employ the Community Earth System Model version 1 (CESM1; Hurrell et al., 2013), which couples
88 atmosphere, ocean, land, and sea ice components. The climate simulations use the Community
89 Atmosphere Model version 5 (CAM5), while the atmospheric chemistry simulations use CAM with
90 Chemistry (CAM-chem), which includes interactive gas-phase chemistry, aerosols, and radiative effects
91 (Lamarque et al., 2012; Tilmes et al., 2015). The chemistry simulations employ the FMOZ compset, with
92 the Model for O₃ and Related chemical Tracers version 4 (MOZART-4) mechanism (Emmons et al.,
93 2010, 2012). This configuration explicitly resolves O₃-NO_x-HO_x-CO-VOC chemistry and is used to
94 diagnose climate-driven changes in surface O₃.
95 The experiments proceed in three stages. Stage I determines the sea salt injection needed to produce the
96 target radiative perturbation. Stage II quantifies the coupled response of sea surface temperature (SST)
97 and sea ice concentration (SIC). Stage III prescribes the resulting SST and SIC fields in CAM-chem to
98 isolate the climate-mediated surface O₃ response (Table 1).

99

100 **Table 1.** Overview of the experimental design.

Stage	Experiment	Compset	SST/SIC	Sea salt injection (Tg yr ⁻¹ per region)
I	CTRL-RAD	F_2000_clim	Prescribed	/
	MCB-RAD			1/2/5/10/15/20/25/30/40
II	CTRL-SST	B_2000_CAM5	Interactive	/
	MCB-SST			11.4
III	CTRL ₅₈₅	FMOZ	CTRL	/
	MCB ₅₈₅		MCB	/

101

102 **2.2 Calibration of sea salt injection**

103 Stage I uses the CESM1 F_2000_clim compset with prescribed present-day climatological SST and SIC
104 (Table 1). Sea salt injection is implemented through the prescribed-emission method described by Yang
105 et al., 2025. Externally generated sea salt mass and number emissions are added to the accumulation
106 mode over six marine regions. These perturbations affect aerosol optical properties, cloud droplet number



107 concentration, cloud liquid water, low-cloud fraction, and shortwave radiation through aerosol–radiation
108 and aerosol–cloud interactions.

109 The six oceanic injection regions follow the MCB-REG model intercomparison protocol (Rasch et al.,
110 2024) and include the Northeast Pacific (NEP), Southeast Pacific (SEP), Southeast Atlantic (SEA), North
111 Pacific (NP), South Pacific (SP), and Northern Ocean (NO) (Figure 1). Each region covers about 4 % of
112 the global ocean area, except 2 % for NO region. Injection is restricted to grid columns with an open-
113 ocean fraction of at least 90%. These domains are research-oriented candidate regions rather than a
114 deployment recommendation. The same annual injection amount is applied to each region to provide a
115 controlled multi-region perturbation.

116 We calibrate the sea salt emission rate against its effective radiative forcing (ERF) to identify the
117 injection required to offset the 2050 ERF difference between SSP5-8.5 and SSP2-4.5. Fixed-SST/SIC
118 experiments add 1, 2, 5, 10, 15, 20, 25, 30, or 40 Tg yr⁻¹ of sea salt in each target region (MCB-RAD),
119 together with a no-injection control (CTRL-RAD). Each experiment is run for 25 years. The first 5 years
120 are discarded as spin-up, and the final 20 years are analyzed. Top-of-atmosphere net radiation and near-
121 surface temperature show no significant drift during the analysis period. A quadratic fit to the sea salt–
122 ERF relationship (Figure S1) yields an injection rate of 11.4 Tg yr⁻¹ per region for an ERF perturbation
123 of -1.0 W m^{-2} , equal in magnitude to the 2050 difference between SSP5-8.5 and SSP2-4.5 (Gidden et
124 al., 2019).

125 **2.3 Coupled SST and SIC responses**

126 Stage II uses fully coupled CESM1 simulations with the B_2000_CAM5 compset and year-2050
127 SSP5-8.5 forcing, including anthropogenic aerosol emissions, greenhouse gas concentrations, and solar
128 forcing following Yang et al. (2016, 2025) and Yu et al. (2026). The aerosol module accepts externally
129 prescribed sea salt mass and number fluxes. Two fully coupled experiments are conducted, including
130 CTRL-SST without SSA injection and MCB-SST with SSA injection of 11.4 Tg yr⁻¹ for each of the six
131 regions. Three initial-condition ensemble members are performed for each experiment from different
132 restart files. Each member is integrated for 300 years with year-2050 emissions repeated annually. The
133 first 150 years are treated as spin-up and the last 150 years are analyzed.



134 **2.4 Atmospheric chemistry experiments**

135 In Stage III, SST and SIC fields from the Stage II coupled climate simulations are prescribed as lower
 136 boundary conditions in CAM-chem. No additional sea salt is introduced, thereby excluding the direct
 137 chemical effects of the injected aerosol and isolating the response to the MCB-induced climate state.
 138 Anthropogenic emissions of O₃ precursors, including nitrogen oxides (NO_x), non-methane volatile
 139 organic compounds (NMVOCs), and carbon monoxide (CO), are prescribed from CMIP6 emission
 140 inventories for 2050 under SSP5-8.5 (O'Neill et al., 2016; Hoesly et al., 2018). Soil NO_x emissions are
 141 kept at present-day levels following Tilmes et al. (2015), while lightning NO_x emissions are calculated
 142 using the parameterization of Price et al. (1997). Future biogenic volatile organic compound (BVOC)
 143 emissions are obtained by linear interpolation of CMIP6 multi-model projections under SSP5-8.5 as
 144 offline input. Biomass burning emissions follow the CMIP6 inventory (van Marle et al., 2017). Methane
 145 (CH₄) is prescribed as a lower-boundary concentration under SSP5-8.5.
 146 To isolate the climate-mediated effect of MCB on surface O₃, we conduct two atmospheric chemistry
 147 experiments with identical SSP5-8.5 precursor emissions but different prescribed SST and SIC fields.
 148 CTRL₅₈₅ uses SST and SIC from CTRL-SST, whereas MCB₅₈₅ uses SST and SIC from MCB-SST. All
 149 simulations are constrained by monthly climatological SST and SIC to fix oceanic boundary conditions
 150 throughout the integration period. The MCB-induced surface O₃ response, denoted as ΔO_{3_MCB} , is
 151 calculated as MCB₅₈₅ minus CTRL₅₈₅. Because precursor emissions are held fixed, this difference
 152 represents the surface O₃ response to the MCB-induced climate changes.

153 The capability of CESM1 to simulate tropospheric O₃ has been extensively evaluated in previous
 154 studies. CESM1 generally reproduces the large-scale spatial distribution and seasonal variability of
 155 tropospheric O₃ and shows reasonable agreement with ozonesonde and satellite observations in the
 156 tropics and Northern Hemisphere. However, regional biases in simulated O₃ remain. For example,
 157 tropospheric O₃ is underestimated by up to 25% in parts of the Southern Hemisphere, partly due to
 158 uncertainties in convection and stratosphere–troposphere exchange processes (Tilmes et al., 2015). In
 159 addition, CAM-chem exhibits persistent summertime surface O₃ biases over North America and Europe,
 160 with O₃ concentrations strongly influenced by meteorological processes and model configuration
 161 (Lamarque et al., 2012; Porter et al., 2017). Systematic errors have also been identified in key O₃



precursor species, including CO, VOCs, NO_x, and PAN, which can propagate into O₃ simulations and future projections (Tilmes et al., 2015). We therefore apply machine learning bias correction before evaluating regional MCB-induced O₃ changes. To improve the consistency between CESM1 outputs and the observational dataset for machine-learning applications, an additional simulation spanning 2012–2019 is carried out, where the years 2012–2013 serve as spin-up. Zonal and meridional winds are nudged toward MERRA-2 reanalysis (Gelaro et al., 2017) with a relaxation timescale of 6 h within this run.

2.5 Observational data

We evaluate the simulated surface O₃ from CESM1 against daily-mean measurements from publicly available routine monitoring networks covering China, the United States, and Europe over 2014–2019. Chinese observations are obtained from the China National Environmental Monitoring Centre (CNEMC) network. American observations are from the U.S. Environmental Protection Agency Air Quality System (EPA AQS). European observations are from the European Environment Agency Air Quality e-Reporting database (EEA). After quality control, the dataset contains 1,674 stations in China, 1,443 in the United States, and 2,799 in Europe.

2.6 Machine learning-based bias correction

We follow Ni et al. (2026) and train regional machine learning models to estimate the CESM1 O₃ correction over 2014–2019. The correction is defined as observed minus simulated surface O₃. Positive corrections indicate model underestimation and negative values indicate overestimation. Learning the correction rather than O₃ itself allows the models to represent systematic errors associated with emissions, chemistry, meteorology, and location.

The predictors include key variables influencing O₃ formation and variability, comprising meteorological parameters (e.g., surface air temperature, relative humidity, winds, boundary layer height, and radiation), chemical precursor concentrations (e.g., NO_x, VOCs, and CO), and spatial information (latitude and longitude) (Table S1). These predictors collectively represent the major processes controlling O₃ production, transport, and removal.

A Light Gradient Boosting Machine (LightGBM) algorithm (Ke et al., 2017) is employed because it can capture complex nonlinear relationships and interactions among predictors. The dataset is divided into



189 training and test sets. Models are evaluated using standard statistical metrics, including the coefficient of
190 determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). Training,
191 hyperparameter tuning, test-set evaluation, and feature-importance diagnostics are described in Text S1.
192 The trained regional models are applied to the CESM1 chemistry simulations. The bias-corrected O_3
193 concentration is then obtained by adding the predicted correction to the raw CESM1 value. The corrected
194 fields are then used to quantify regional MCB-induced O_3 responses.

195 **2.7 Statistical interpretation of meteorological controls**

196 A second set of LightGBM models is used to identify the meteorological variables most closely
197 associated with the simulated spatial variability of the bias-corrected MCB-induced surface O_3 response.
198 The bias-corrected response to MCB-induced climate change, denoted as ΔO_{3_MCBc} , is used as the target
199 variable, while the corresponding changes in meteorological variables are used as predictors.
200 Independent models are trained for China, Europe, and the United States using grid-cell samples within
201 each region. Model hyperparameters are optimized through cross-validation, and predictive performance
202 is evaluated using an independent test dataset.

203 To interpret the trained models, SHapley Additive exPlanations (SHAP) are applied to quantify the
204 contribution of each predictor to the model prediction at each grid cell. Mean absolute SHAP values are
205 then normalized to compare the relative predictive importance of individual variables and process groups
206 within each region. For physical interpretation, meteorological variables are further classified into five
207 process-based groups that characterize the primary meteorological pathways linking MCB-induced
208 climate changes to surface O_3 variations, including thermal conditions (TS, surface temperature),
209 moisture (QREFHT, near-surface specific humidity; RH, relative humidity; PRE, precipitation),
210 radiation and cloud processes (FSNS, net surface shortwave radiation; CL, cloud fraction), boundary-
211 layer mixing (PBLH, planetary boundary layer height; PS, surface pressure), and atmospheric transport
212 (U and V, horizontal winds; OMEGA, vertical pressure velocity).

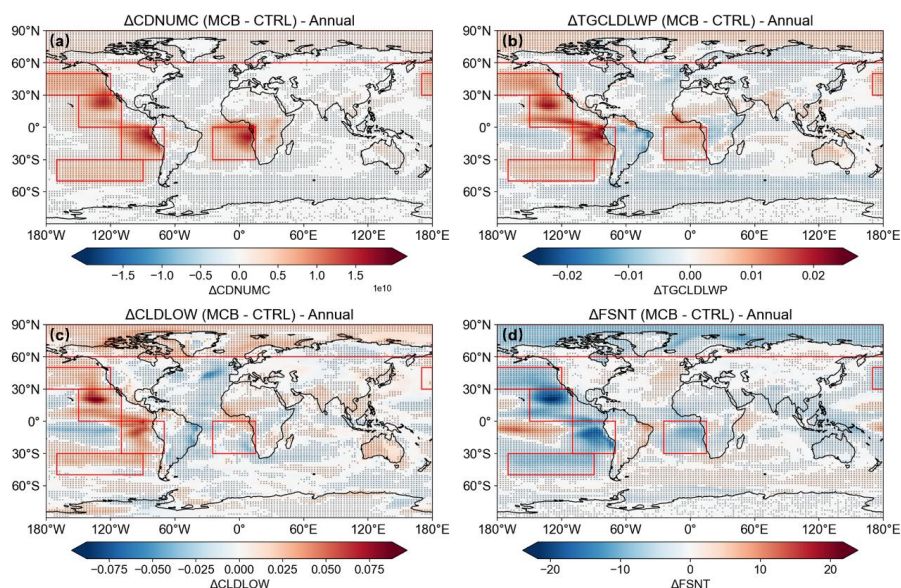


213 **3 Results**

214 **3.1 SST and SIC responses to global MCB deployment**

215 Marine cloud brightening induces a coherent chain of cloud and radiation responses over the injection
 216 regions (Figure 1). Sea salt injection substantially increases cloud droplet number concentration
 217 (CDNUMC), consistent with enhanced availability of cloud condensation nuclei. The elevated
 218 CDNUMC suppresses precipitation efficiency, leading to an increase in total cloud liquid water path
 219 (TGCLDLWP) and an enhancement of low cloud fraction (CLDLWP). The combined increase in cloud
 220 water content and low-cloud coverage strengthens shortwave cloud radiative effects, resulting in a
 221 pronounced reduction in net shortwave radiation at the top of the atmosphere (FSNT), providing the
 222 radiative perturbation that drives the coupled SST and SIC responses.

223 The reduced shortwave energy input leads to a significant cooling of SST, with a global mean
 224 decrease of $-0.44\text{ }^{\circ}\text{C}$ annually and enhanced cooling by $-0.59\text{ }^{\circ}\text{C}$ in the tropics (30°S – 30°N) (Figure 2).
 225 The strongest SST decreases occur in the tropical regions and the Northern Hemisphere high latitudes,
 226 where MCB is deployed. Regionally, SST responses range from strong cooling exceeding $-1.62\text{ }^{\circ}\text{C}$ to
 227 localized warming of about $1.29\text{ }^{\circ}\text{C}$, indicating that the coupled response is spatially heterogeneous. SIC
 228 increases over polar regions, with an Arctic annual mean enhancement of 9.7% and local increases
 229 exceeding 16.5%. The stronger Northern Hemisphere SIC response reflects the placement of the injection
 230 regions together with differences in ocean heat capacity, land-sea configuration, and ice-albedo feedback.
 231 Together, these results link MCB-induced cloud microphysical changes to reduced shortwave radiation,
 232 lower SST, and increased SIC.



233

234 **Figure 1.** Annual mean differences between MCB-SST and CTRL-SST in (a) cloud droplet number
235 concentration (CDNUMC), (b) total cloud liquid water path (TGCLDLWP), (c) low-cloud fraction
236 (CLDLWP), and (d) net shortwave radiation at the top of the atmosphere (FSNT). Stippling marks grid
237 cells with $p < 0.05$ based on independent two-sample t-tests. Red boxes show the six MCB-REG injection
238 regions (NEP, 0–30°N and 110–150°W; SEP, 0–30°S and 70–110°W; SEA, 0–30°S and 25°W–15°E;
239 NP, 30–50°N and 170°E–120°W; SP, 30–50°S and 90–170°W; NO, 60–90°N and all longitudes).

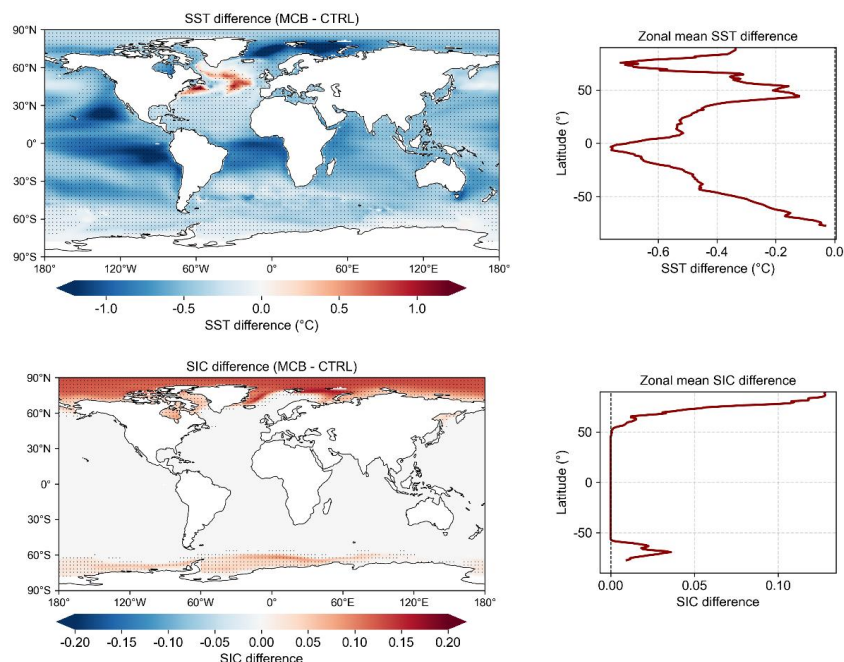


Figure 2. Spatial distribution (left) and zonal mean (right) differences in annual SST (top) and SIC (bottom) between MCB-SST and CTRL-SST simulations. Stippling marks grid cells with $p < 0.05$ based on independent two-sample t-tests.

3.2 Surface ozone responses to MCB-induced SST and SIC changes

The MCB-induced changes in SST and SIC, together with associated atmospheric and meteorological adjustments, alter the meteorological environment in which atmospheric chemistry occurs. We next examine how these climate adjustments induce changes in surface O_3 in boreal summer, when photochemical O_3 production is strongest and surface O_3 commonly reaches its seasonal maximum over Northern Hemisphere land. The two chemistry experiments show similar surface O_3 patterns, with high surface O_3 over subtropical and midlatitude land in the Northern Hemisphere, persistent maxima over North Africa, the Middle East, and South to East Asia, and low values over the tropical Pacific and Southern Hemisphere oceans (Figure S2). The high O_3 belt expands from boreal spring into summer. Compared to this background, MCB-induced climate change produces a spatially heterogeneous surface O_3 response during boreal summer (Figure 3). O_3 increases are strongest across tropical and subtropical



regions, whereas land areas in South and East Asia exhibit mean decreases of 1.72 and $0.78 \mu\text{g m}^{-3}$, respectively. These regional contrasts reflect differences in chemical regimes and transport conditions, as well as their responses to MCB-driven changes in temperature, humidity, cloud cover, and boundary-layer structure.

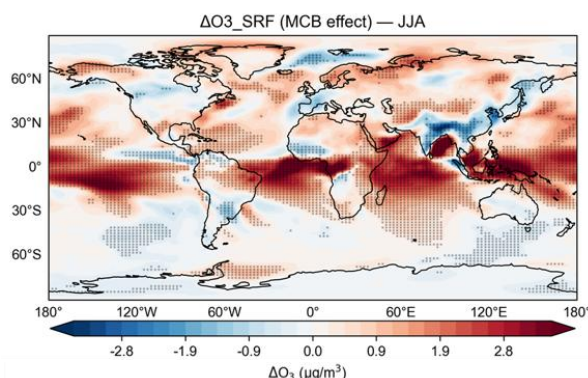


Figure 3. Changes in surface O_3 concentrations due to MCB-induced climate change ($\Delta\text{O}_{3\text{MCB}}$, $\mu\text{g m}^{-3}$) during boreal summer (June to August). Stippling indicates grid cells with $p < 0.05$ based on a two-sided one-sample t-test of paired MCB-CTRL differences.

To investigate the meteorological drivers of this spatial heterogeneity, Figures 4 and S3 show the atmospheric responses to MCB-driven changes in SST and SIC. These responses are characterized by widespread surface cooling and regionally varying changes in moisture, cloud cover, boundary-layer structure, and atmospheric circulation. By altering temperature-dependent reaction rates and moisture-sensitive HO_x chemistry, these meteorological changes modify O_3 production and loss (Figure 5). The positive O_3 anomalies across many tropical and subtropical regions (Figure 3) are generally associated with atmospheric drying, consistent with reduced water vapor-dependent chemical loss of O_3 .

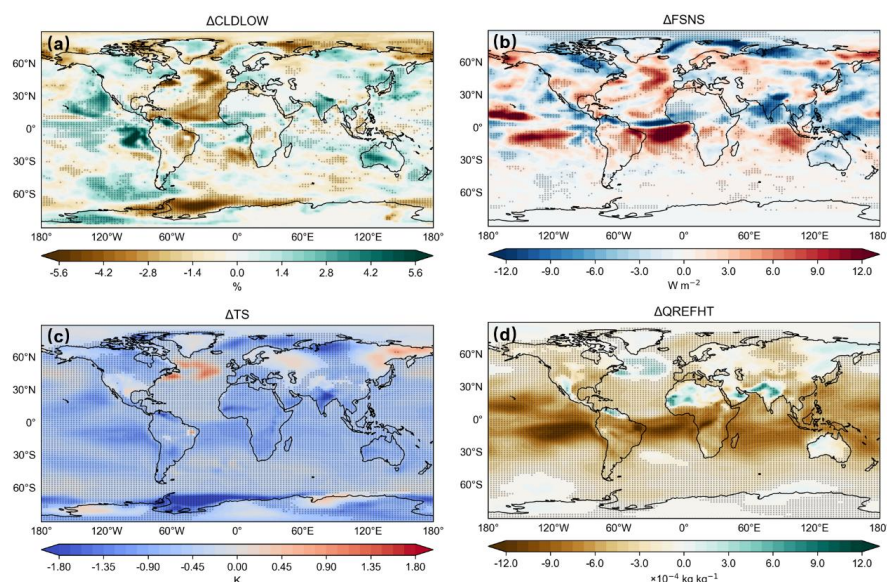


Figure 4. Changes in low cloud fraction (ΔCLDLow), net surface shortwave radiation (ΔFSNS , W m^{-2}), surface temperature (ΔTS , K) and near-surface specific humidity (ΔQREFHT , kg kg^{-1}) due to MCB-induced climate change during boreal summer. Stippling indicates grid cells with $p < 0.05$ based on a two-sided one-sample t-test of paired MCB-CTRL differences.

Over eastern China and parts of North America and Europe, where precursor levels are relatively high, the negative O_3 anomalies coincide with MCB-induced surface cooling and reduced chemical O_3 production, indicating that the suppression of temperature-sensitive photochemistry represents an important contributor to the ozone response in these polluted regions. Although atmospheric drying may simultaneously weaken radical cycling and chemical O_3 loss, this compensating effect is insufficient to offset the reduction in chemical ozone production.

Over South Asia, by contrast, O_3 reductions are linked to coordinated changes in near-surface moisture, cloud cover, and radiation. Increased moisture is accompanied by greater low-cloud cover and reduced surface shortwave radiation, which suppress photolysis and weaken O_3 production. The concurrent decreases in OH and HO_2 (Figure S3) and in the O_3 production rate (Figure 5) further indicate reduced oxidation and photochemical activity. Under these cloudier, lower-radiation conditions, the moisture-driven enhancement of chemical O_3 loss remains comparatively weak, leaving suppressed production as the dominant influence on the O_3 response in South Asia.



Beyond these chemical pathways, MCB-driven dynamical changes in planetary boundary-layer height, low-level winds, and atmospheric circulation (Figure S4) may further influence surface O_3 through vertical mixing, dilution, and regional transport. Taken together, the spatial pattern of the O_3 response arises from the combined effects of chemical and dynamical processes. Cooling and reduced radiation suppress photochemical production, moisture changes modify HO_x -mediated production and loss, and boundary-layer and circulation responses redistribute O_3 . We therefore next examine the responses over China, Europe, and the United States to further identify the meteorological factors underlying this regional heterogeneity.

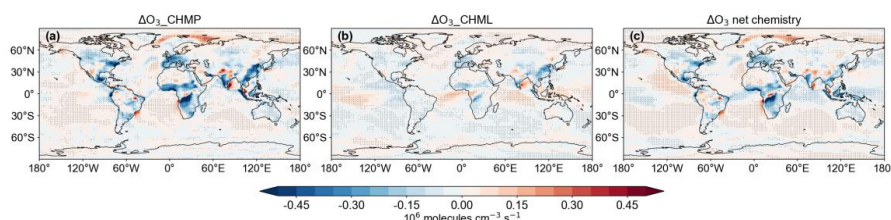


Figure 5. Changes in O_3 chemical production (ΔO_3_CHMP), chemical loss (ΔO_3_CHML) and net O_3 chemical tendency ($\times 10^6$ molecules $cm^{-3} s^{-1}$) caused by the MCB-induced climate change during boreal summer. Stippling indicates grid cells with $p < 0.05$ based on a two-sided one-sample t-test of paired MCB-CTRL differences.

3.3 Regional ozone responses and bias correction

To complement the global analysis, we focus on China, Europe, and the United States, three major Northern Hemisphere regions with extensive surface O_3 monitoring networks and contrasting atmospheric environments. Because CESM1 exhibits substantial and regionally heterogeneous biases in surface O_3 , the LightGBM-based bias correction was applied independently to each of the two chemistry simulations. Separate regional models were trained for China (20–55°N, 70–137°E), Europe (35–70°N, 10°W–40°E), and the United States (25–50°N, 65–125°W). For each region, all regional averages were calculated based solely on the masked grid cells falling within the national borders. Details of the training procedure, hyperparameter optimization, test-set performance, and feature-importance analysis are provided in Text S1, with summary statistics in Table S2 and diagnostic results in Figure S5.



312 Figures S6–S7 compare the raw and bias-corrected surface O_3 fields for the CTRL₅₈₅ and MCB₅₈₅
313 simulations, with the corresponding corrections predicted by the bias correction model relative to the raw
314 CESM1 values. Negative bias corrections indicate that CESM1 overestimates surface O_3 , whereas
315 positive values indicate underestimation. The corrections are predominantly negative over Europe and
316 the United States, where the bias-corrected regional means are approximately 35–40 $\mu g m^{-3}$ lower than
317 the raw simulations. Smaller reductions of 20 $\mu g m^{-3}$ are found over China. The magnitude and sign of
318 the correction nevertheless vary considerably within each region. In China, for example, the regional
319 mean correction is negative, but positive corrections occur in parts of eastern China with localized
320 underestimation by CESM1. These regional patterns are broadly consistent with the CESM2 biases
321 reported by Ni et al. (2026).

322 Given the substantial regional biases in CESM1 surface O_3 , we use the bias-corrected fields to assess the
323 regional climate-mediated response to MCB. Figure 6 compares the raw and corrected MCB effects,
324 denoted as ΔO_{3_MCB} , over China, Europe, and the United States. At the regional scale, bias correction
325 affects the estimated MCB response differently across the three regions. The raw CESM1 estimates are
326 $-0.36 \mu g m^{-3}$ for China, $+0.33 \mu g m^{-3}$ for Europe, and $+0.03 \mu g m^{-3}$ for the United States, whereas the
327 corrected responses are -0.33 , $+0.01$, and $+0.12 \mu g m^{-3}$, respectively. Thus, MCB exerts regionally
328 differentiated climate-mediated effects on surface O_3 , underscoring the importance of incorporating
329 regional air quality responses into assessments of MCB deployment.

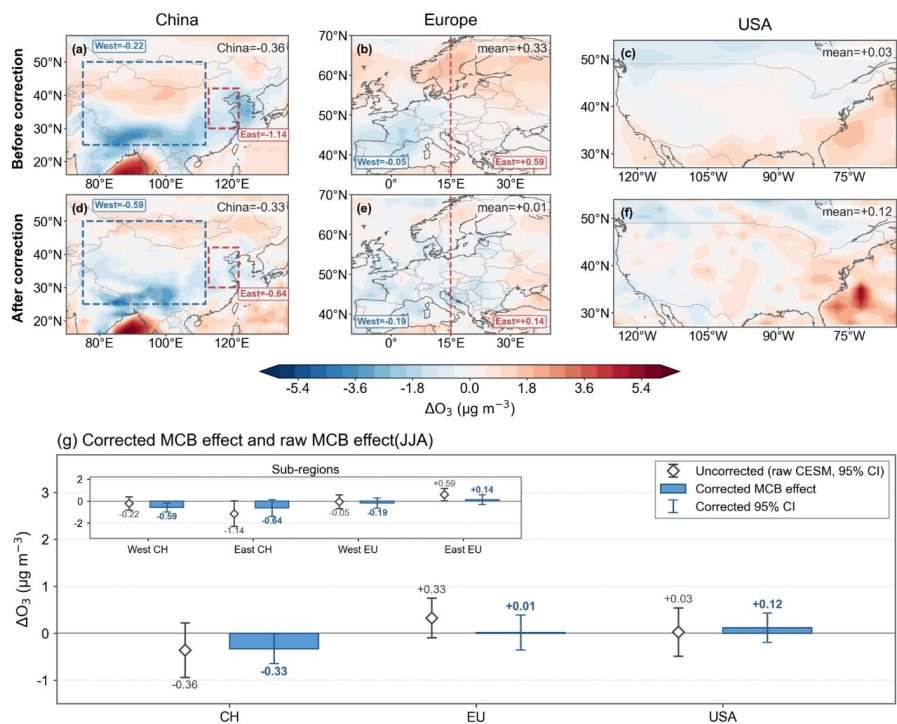
330 The subregional results reveal stronger spatial contrasts. Before bias correction, the MCB responses over
331 western and eastern China are -0.22 and $-1.14 \mu g m^{-3}$, respectively. After correction, the corresponding
332 values become -0.59 and $-0.64 \mu g m^{-3}$, substantially reducing the east–west contrast while retaining
333 negative responses in both subregions. Over Europe, the raw responses are $-0.05 \mu g m^{-3}$ in the west and
334 $+0.59 \mu g m^{-3}$ in the east, compared with corrected values of -0.19 and $+0.14 \mu g m^{-3}$. Bias correction
335 therefore weakens the east–west contrast over Europe but preserves the difference in sign. These results
336 highlight a limitation of regional mean estimates, which can obscure substantial or even opposing
337 subregional responses, as illustrated by the offsetting changes over western and eastern Europe. This
338 limitation underscores the need to examine MCB-induced O_3 responses and their meteorological controls
339 at finer spatial scales.



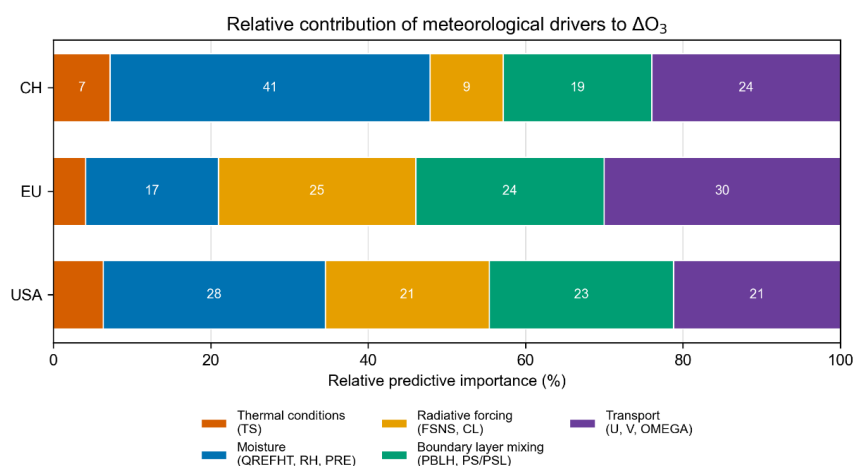
340 To identify the meteorological variables associated with these spatial differences, separate LightGBM
341 models were trained for China, Europe, and the United States using the bias-corrected ΔO_{3_MCBc} as the
342 target and MCB-induced meteorological changes as predictors. The models reproduced the spatial
343 variability of ΔO_{3_MCBc} with R^2 values of 0.69 for China, 0.68 for Europe, and 0.52 for the United States
344 on the held-out test set. The selected predictors therefore explain a substantial fraction of the simulated
345 spatial variability over China and Europe, whereas the lower performance over the United States
346 indicates greater unexplained variability and warrants more cautious interpretation.

347 The SHAP analysis further reveals pronounced regional differences in the relative importance of
348 the five meteorological predictor groups within the model-explained spatial variability of ΔO_{3_MCBc}
349 (Figure 7). Over China, moisture-related variables account for 41% of the total importance, exceeding
350 transport at 24% and boundary-layer mixing at 19%. This result indicates that changes in atmospheric
351 moisture are most strongly associated with the spatial variability of the MCB-induced O_3 response over
352 China. Over Europe, transport has the highest relative importance at 30%, followed by radiation and
353 cloud processes at 25% and boundary-layer mixing at 24%. Over the United States, the importance is
354 more evenly distributed among moisture at 28%, boundary-layer mixing at 23%, and radiation and cloud
355 processes at 21%.

356 These SHAP-based importance rankings represent statistical associations with the model-explained
357 spatial variability rather than direct causal attribution of the O_3 response. Nevertheless, they are
358 consistent with the process-based interpretation of the CESM1 results and indicate that the
359 meteorological influences associated with MCB vary among regions. Moisture changes are most closely
360 associated with the simulated response over China, transport and radiation play larger roles over Europe,
361 and multiple meteorological processes contribute comparably over the United States.



362
363 **Figure 6.** Spatial distributions and regional means of the climate-mediated surface O₃ response to MCB
364 during boreal summer. Panels (a–c) show the raw CESM1 responses over China, Europe, and the United
365 States, and panels (d–f) show the corresponding bias-corrected responses. Panel (g) compares the bias-
366 corrected regional means shown by blue bars with the raw CESM1 estimates shown by black diamonds.
367 Error bars indicate 95% confidence intervals for both the bias-corrected and raw responses. The inset
368 presents the corresponding results for western and eastern China and western and eastern Europe. The
369 subregional domains are western China at 75–112°E and 25–50°N, eastern China at 113–122°E and 30–
370 42°N, western Europe at 10°W–15°E and 35–70°N, and eastern Europe at 15–40°E and 35–70°N.



371

372 **Figure 7.** Relative predictive importance of grouped meteorological predictors in the LightGBM models
 373 of the bias-corrected MCB-induced surface O_3 response. The predictor groups comprise thermal
 374 conditions represented by TS, moisture represented by QREFHT, RH, and PRE, radiation and cloud
 375 processes represented by FSNS and CL, boundary-layer mixing represented by PBLH and PS, and
 376 atmospheric transport represented by U, V, and OMEGA. The stacked bars show normalized mean
 377 absolute SHAP values, with each group expressed as a percentage of the total mean absolute SHAP
 378 importance in China (CH), Europe (EU), and the United States (USA).

379

380 **4 Discussions and Conclusions**

381 This study isolates the climate-mediated influence of global MCB deployment on surface O_3 . Sea salt
 382 emissions alter cloud properties and shortwave radiation, decreasing global annual mean SST by 0.44 °C
 383 and tropical SST by 0.59 °C, while increasing annual Arctic mean SIC by 9.7%. The resulting changes
 384 in temperature, moisture, radiation, boundary-layer mixing, and circulation affect O_3 production, loss,
 385 and transport. During boreal summer, O_3 increases across many tropical and subtropical regions but
 386 decreases by 1.72 and 0.78 $\mu g m^{-3}$ over South and East Asia, respectively. The negative response over
 387 eastern China is associated with cooling and reduced chemical production, whereas tropical increases are



388 linked to drying and weaker O₃ loss. Over South Asia, increased moisture, cloud cover, and reduced
389 radiation suppress photochemical O₃ production.

390 After bias correction, the summer mean O₃ responses are $-0.33 \mu\text{g m}^{-3}$ over China, $+0.01 \mu\text{g m}^{-3}$ over
391 Europe, and $+0.12 \mu\text{g m}^{-3}$ over the United States. The near-zero European mean partly results from
392 opposing responses of $-0.19 \mu\text{g m}^{-3}$ in western Europe and $+0.14 \mu\text{g m}^{-3}$ in eastern Europe. Western and
393 eastern China both show substantial O₃ decreases. These results show that regional means can obscure
394 stronger or opposing subregional responses, highlighting the need for finer-scale assessment of MCB-
395 related air quality changes.

396 The meteorological response models explain 69%, 68%, and 52% of the spatial variability in the bias-
397 corrected MCB-induced O₃ response over China, Europe, and the United States, respectively. Moisture-
398 related variables have the highest predictive importance over China at 41%, indicating their close
399 association with spatial variations rather than the regional mean decrease. The negative response over
400 eastern China remains linked to cooling-induced suppression of O₃ production. Over Europe, transport
401 has the highest importance at 30%, consistent with the east–west contrast, whereas moisture, boundary-
402 layer mixing, and radiation contribute comparably over the United States.

403 Several limitations of this study should be noted. First, the bias-correction models are trained using
404 historical observations and are then applied to future meteorological and chemical conditions. Although
405 the raw and corrected results generally retain similar regional response patterns, uncertainty in the bias
406 correction may influence the magnitude of the O₃ response. Future work should quantify this uncertainty
407 using temporally and spatially blocked cross-validation, out-of-distribution diagnostics, and explicit
408 uncertainty propagation. Second, the SHAP analysis identifies statistical associations rather than direct
409 physical contributions. Meteorological predictors are dynamically coupled, and their relative importance
410 cannot be interpreted as independent causal effects on O₃. Sensitivity experiments and more complete
411 chemical budget diagnostics are needed to separate the influences of temperature, moisture, radiation,
412 boundary-layer mixing, and transport. Third, the results are based on CESM1 and a single simultaneous
413 deployment strategy over six oceanic regions. The magnitude and spatial pattern of the response may
414 depend on model configuration, injection location, injection intensity, and background climate conditions.
415 Multi-model experiments and alternative deployment strategies are therefore needed to evaluate the



416 robustness of the identified responses. Finally, the current experimental design excludes the direct
417 chemical effects of injected SSA, including halogen activation, heterogeneous N_2O_5 hydrolysis, HO_2
418 uptake, and aerosol-induced changes in photolysis. Fully coupled chemistry-climate experiments with
419 explicit sea salt perturbations are required to quantify the combined climate-mediated and direct chemical
420 effects.

421 Overall, simultaneous MCB deployment across six oceanic regions produces substantial changes in the
422 physical climate system and a spatially heterogeneous response in surface O_3 . The corrected regional
423 mean changes range from $-0.33 \mu\text{g m}^{-3}$ over China to $+0.12 \mu\text{g m}^{-3}$ over the United States, while stronger
424 and even opposing responses emerge at subregional and local scales. The contrasting responses across
425 China, Europe, the United States, South Asia, and tropical regions demonstrate that the air quality
426 consequences of MCB cannot be inferred from global cooling alone. By extending the assessment of
427 MCB from physical climate variables to atmospheric composition, this study identifies regional air
428 quality as an essential component of evaluating the broader consequences and trade-offs of climate
429 intervention.

430

431 **Code and data availability**

432 Surface ozone observations over China can be obtained from the China National Environmental
433 Monitoring Centre (<http://www.cnemc.cn>). In Europe, surface ozone data encompassing 36 countries are
434 available from the European Environment Agency
435 <https://discomap.eea.europa.eu/map/fme/AirQualityExport.html>. In United States, surface ozone
436 measurements are sourced from the United States Environmental Protection Agency
437 (https://aqs.epa.gov/aqsweb/airdata/download_files.html#Daily; EPA, 2023). The processed modeling
438 data are available at <https://doi.org/10.5281/zenodo.22297789>.

439 **Author contributions**

440 Yang Yang designed the research; Yiqian Ni performed the simulations and analyzed the data. All
441 authors discussed the results and wrote the paper.



442 **Competing interests**

443 At least one of the (co-)authors is a member of the editorial board of Atmospheric Chemistry and Physics.

444 The authors have no other competing interests to declare.

445

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