1 **Effects of climate change, CO₂ and O₃ on wheat productivity in Eastern China,**
2 **singly and in combination**

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18 **Abstract.** Air pollution and climate change are increasing threats to agricultural
19 production and food security. Extensive studies have focused on the effect of climate
20 change, but the interactive effects of multiple global change factors are poorly
21 understood. Here, we incorporate the interactions between climate change, carbon
22 dioxide (CO₂) and ozone (O₃) into an eco-physiological mechanistic model based on
23 three years of O₃ Free-Air Concentration Elevation (O₃-FACE) experiments. We then
24 investigate the effects of climate change, elevated CO₂ concentration ([CO₂]) and

rising O₃ concentration ([O₃]) on wheat growth and productivity in eastern China in 1996–2005 (2000s) and 2016–2025 (2020s) under two climate change scenarios, singly and in combination. We find the interactive effects of climate change, CO₂ and O₃ on wheat productivity have spatially explicit patterns; the effect of climate change dominates the general pattern, which is however subject to the large uncertainties of climate change scenarios. Wheat productivity is estimated to increase by 2.8–9.0% due to elevated [CO₂] however decline by 2.8–11.7% due to rising [O₃] in the 2020s, relative to the 2000s. The combined effects of CO₂ and O₃ are less than that of O₃ only, on average by 4.6–5.2%, however with O₃ damage outweighing CO₂ benefit in most of the region. This study demonstrates a more biologically meaningful and appropriate approach for assessing the interactive effects of climate change, CO₂ and O₃ on crop growth and productivity. Our findings promote the understanding on the interactive effects of multiple global change factors across contrasting climate conditions, cast doubt on the potential of CO₂ fertilization effect in offsetting possible negative effect of climate change on crop productivity as suggested by many previous studies.

Keywords: air pollution; climate change; CO₂ fertilization; crop; ozone; risk

1. Introduction

Air pollution and climate change are increasing threats to agricultural production and food security (Ainsworth, 2008; Long, 2012; Burney and Ramanathan, 2014; Porter et al., 2014; Tai et al., 2014), particularly in India and China (Avnery et al., 2013; Tang et al., 2013; Burney and Ramanathan, 2014). Extensive studies have focused on the effect of climate change (Porter et al., 2014), however the interactive effects of

multiple global change factors, such as climate change, elevated carbon dioxide (CO₂) concentration ([CO₂]) and rising tropospheric ozone (O₃) concentration ([O₃]), are poorly understood (Ainsworth, 2008; Long, 2012; Burney and Ramanathan, 2014; Porter et al., 2014; Tai et al., 2014). Climate change has been changing the magnitude and distribution of seasonal temperature and precipitation, as well as their inter-annual variability, directly and indirectly affecting agricultural production worldwide (Lobell et al., 2008; Challinor et al., 2014; Porter et al., 2014). Elevated [CO₂] is expected to increase plant photosynthesis and reduce transpiration (Kimball et al., 1995, 2016; Ainsworth, 2008), which is reported to offset possible negative effects of climate change in many previous studies (Porter et al., 2014). However, emissions of CO₂ are usually accompanied by O₃ precursors which have driven a rise in tropospheric [O₃] (Burney and Ramanathan, 2014; IPCC, 2014). Tropospheric [O₃] has risen from a global average of 10–15 to 30–50 ppb over the past 150 years (IPCC, 2014). O₃ is the most harmful to forests and crops among common air pollutants (Paoletti and Manning, 2007). Numerous controlled experiments with both open-top chamber and Ozone Free-Air Concentration Elevation (O₃-FACE) platforms have documented that chronic exposure to O₃ at levels above 40 ppb generally reduces stomatal conductance and impairs the activity of photosynthetic enzymes (The Royal Society, 2008; Wang et al., 2012), although increases in stomatal conductance have been observed in some cases (Wilkinson and Davies, 2010). Rising O₃ reduces carbon assimilation rates and leaf area, accelerates respiration increases and leaf senescence, leading to a reduction in crop productivity (Feng et al., 2008, 2011).

Recently, there have been increasing efforts to assess the risk of O₃, either singly or combined with climate change, on food production at a regional or global scale.

73 However, most of the studies use the empirical exposure-based and/or flux-based
74 approaches (Avnery et al., 2011a,b, 2013; Mills et al., 2011; Tang et al., 2013; Burney
75 and Ramanathan, 2014; Tai et al., 2014; McGrath et al., 2015). The empirical
76 exposure-based approaches, such as those based on AOT40 (hourly accumulated O₃
77 exposure over a threshold of 40 ppb), have been widely applied during the last two
78 decades. These approaches don't consider the biological and climatic factors
79 influencing daytime stomatal O₃ uptake (Danielsson et al., 2003; Pleijel et al., 2004,
80 2007; Feng et al., 2012; Anav et al., 2016). The flux-based approaches have recently
81 been developed, in which the Jarvis-type multiplicative stomatal conductance (g_{sc})
82 models are parameterized to derive relationships between yield loss and stomatal O₃
83 flux (Danielsson et al., 2003; Pleijel et al., 2004, 2007; Feng et al., 2012; Anav et al.,
84 2016). The flux-based approaches are more biologically meaningful and appropriate
85 than the exposure-based approaches in evaluating the risk of O₃ damage, because the
86 factors that affect the O₃ flux to stomata such as multiple climatic variables and crop
87 characteristics rather than only [O₃] are considered (Uddling et al., 2004; Pleijel et al.,
88 2004, 2007; LRTAP Convention, 2010; Anav et al., 2016). Nevertheless, such a flux-
89 based approach, which is actually a separate module of a crop model, doesn't
90 sufficiently account for the interactions between crop growth, environment and
91 management. Furthermore, the Jarvis-type multiplicative stomatal conductance model
92 has been widely replaced by the more mechanistic photosynthesis model of Farquhar
93 et al (1980).

94 The interactive effects of O₃ with other environmental factors such as CO₂,
95 temperature, vapor pressure deficit, solar radiation and soil moisture are very
96 important, but nonlinear, poorly understood and difficult to quantify (Fiscus et al.,

2005; Long, 2012). For example, O₃ and CO₂ individually have respectively negative and positive effects on C3 plants generally (Ainsworth, 2008; Gillespie et al., 2012), but their combined effects may compensate for each other (Ainsworth, 2008). Wheat yield losses could be greater when elevated O₃ coincides with high temperature during grain filling period when elevated O₃ causes premature leaf senescence (Long, 2012; Feng et al., 2008, 2011). Abundant solar radiation and adequate water supply are favorable for both crop production and O₃ formation. Therefore, the effects of O₃ on crops should be quantified in a setting with the interactions between crop growth, environment and management (Long, 2012). The eco-physiological mechanistic models that include photosynthesis and stomatal conductance coupling mechanisms, when parameterized with O₃-FACE experiment data, should be the best approach to evaluate and predict the interactive effects of climate change, CO₂ and O₃ on crop production at a regional scale (Anav et al., 2016). However, such approaches have rarely been developed, which have recently been identified as a major research priority in the Agricultural Model Intercomparison and Improvement Project (AgMIP, www.agmip.org).

Since the 1980s, China has had the greatest share of world wheat production, averaging 120.4 Mt annually during 2010–2014. However, O₃ pollution and its effects are severe (Avnery et al., 2011a, b; Tang et al., 2013). Here, we incorporate and parameterize O₃ effects on wheat growth and productivity in an eco-physiological mechanistic model MCWLA-Wheat 2.0 (Tao et al., 2009; Tao and Zhang, 2013) based on three years of O₃-FACE experiments conducted in eastern China (Feng et al., 2011; Zhu et al., 2011) (Fig. 1). We then investigate the interactive effects of climate change, elevated [CO₂] and rising [O₃] on wheat growth and productivity during the

decade around 2000 (2000s) and the decade around 2020 (2020s) in the major wheat production region, which includes eight provinces and accounts for more than 60% of wheat production in China (Fig. 1).

2. Material and methods

2.1. Description of the ecophysiological mechanistic model MCWLA-Wheat 2.0

The process-based general Model to capture the Crop–Weather relationship over a Large Area (MCWLA) for wheat (MCWLA-Wheat) is designed to investigate the impacts of weather and climate variability on crop growth and productivity at a large scale (Tao et al., 2009; Tao and Zhang, 2013). The MCWLA simulates crop response to elevated CO₂, water availability and temperature by adopting a photosynthesis–stomatal conductance coupling mechanism. MCWLA-Wheat has been well validated and applied in major wheat production regions around the world (Tao et al., 2009; Tao and Zhang, 2013; Asseng et al., 2013, 2015). It adopts the robust, process-based representation of the coupled CO₂ and H₂O exchanges in the Lund–Postdam–Jena dynamic global vegetation models (Sitch et al., 2003). The biochemical model of leaf photosynthesis (Farquhar et al., 1980; Von Caemmerer and Farquhar, 1981) is adopted. Net assimilation (A_n) at leaf level is calculated as leaf gross photosynthesis (A_g) and respiration rate (R):

$$A_n = A_g - R \quad (1)$$

The Rubisco-limited rate of photosynthesis (A_c) is given by

$$A_c = \frac{(p_i - \Gamma^*) V_{cmax}}{p_i + K_c \left(1 + \frac{p_i^2}{K_o}\right)} \quad (2)$$

Where, V_{cmax} is the maximum carboxylation velocity, Γ^* is the CO₂ compensation point in the absence of respiration, K_c and K_o are the Rubisco Michaelis–Menten constants for CO₂ and O₂, p_i is the intercellular partial pressure of CO₂ (Pa) and pO_2 is the ambient partial pressure of O₂ (Pa).

Leaf photosynthesis at sub-saturating light intensities (A_j) is given by

$$A_j = \alpha f_{temp} \frac{(p_i - \Gamma^*)J}{p_i + 2\Gamma^*} \quad (3)$$

Where, α is effective ecosystem-level quantum efficiency, f_{temp} is a temperature inhibition function limiting photosynthesis at low and high temperature, and J is the rate of photosynthetic electron transport.

Gross photosynthesis (A_g in g C m⁻²) is given by

$$A_g = \frac{A_j + A_c - \sqrt{(A_j + A_c)^2 - 4\theta A_j A_c}}{2\theta} \quad (4)$$

Where, θ is the curvature of the hyperbolic function.

The photosynthesis model is coupled with a semi-empirical model of stomatal conductance (g_{sc}) for CO₂ as

$$g_{sc} = g_{min} + \frac{1.6A_{dt}}{c_a(1-\lambda_i)} \quad (5)$$

Where, g_{min} is the minimum stomatal conductance, c_a is ambient mole fraction of CO₂, A_{dt} is daytime assimilation rate and λ_i is a parameter balancing the intercellular partial pressure of CO₂ and the ambient partial pressure of CO₂.

2.2. Incorporating the effects of O₃ on crop growth and productivity into the

MCWLA-Wheat model

Substantial controlled experiments have indicated that rising $[O_3]$ induces inhibition of leaf photosynthetic rates by reducing the Rubisco-limited rate of photosynthesis (A_c) and the rate of photosynthetic electron transport (J) (Feng et al., 2011), as well as accelerates premature leaf senescence (Feng et al., 2008, 2011). These major impact mechanisms, as well as the recovery mechanism of young leaves from O_3 damage (Pell *et al.*, 1992, 1997), are incorporated into MCWLA-Wheat by revising the methods of Ewert and Porter (2000) and further parameterized based on three years of O_3 -FACE experiment data in the study area (Feng et al., 2011; Zhu et al., 2011). High O_3 fluxes directly reduce the A_c , as well as the electron transport limited rate (A_j), as

$$A_c = \frac{(p_i - \Gamma^*) V_{cmax}}{p_i + K_c (1 + pO_2/K_o)} f_{O_3,s}(d) \quad (6)$$

Where, $f_{O_3,s}(d)$ is an O_3 effect factor for a day.

$$A_j = \alpha f_{temp} \frac{(p_i - \Gamma^*) J}{p_i + 2\Gamma^*} f_{O_3,s}(d) \quad (7)$$

O_3 uptake through stomata is calculated as

$$O_{3,up} = O_{3,a} g_{sc} f_{O_3,d} \quad (8)$$

Where, $O_{3,up}$ is the uptake rate corrected for differences in the diffusivities of CO_2 and O_3 in air by $f_{O_3,d}$ (Laisk et al., 1989) ($f_{O_3,d} = 0.93$ in this study), and $O_{3,a}$ is the $[O_3]$ at leaf surface.

In line with Wittig et al (2007), A_c and A_j decrease with O_3 uptake rate, represented by the factor $f_{O_3,s}$ which is calculated for every hour as

$$f_{o3,s}(h) = \left\{ \begin{array}{ll} 1; & \text{if } O_{3,up} \leq \gamma_1/\gamma_2 \\ 1 + \gamma_1 - \gamma_2 O_{3,up}; & \text{if } \gamma_1/\gamma_2 < O_{3,up} < (1 + \gamma_1)/\gamma_2 \\ 0; & \text{if } O_{3,up} \geq (1 + \gamma_1)/\gamma_2 \end{array} \right\} \quad (9)$$

Where, the γ_1 and γ_2 are empirical coefficients. γ_1 takes into account that low O_3 concentrations are detoxified without direct effects on photosynthesis ($\gamma_1 = 0.06$ in this study). The coefficient γ_2 describes decrease in A_c per unit of O_3 flux, with $\gamma_2 = 0.015$ ($\text{nmol m}^{-2} \text{s}^{-1}$)⁻¹ in this study.

Repair of O_3 damage is simulated during the night (Amthor, 1988), and the capacity to recover from O_3 damage depends on leaf age, which is simulated as suggested by Ewert and Porter (2000). In addition, O_3 accelerates leaf senescence, affects green leaf area index (LAI) and indirectly reduces photosynthesis rate. Based on Tao and Zhang (2013), we simulate the effects of O_3 on daily green LAI change after anthesis as

$$\frac{\partial \text{LAI}}{\partial t} = \left(\frac{\partial \text{LAI}_{dg}}{\partial t} \right) \max \left(1 + \left(1 - \frac{S}{S_{cr}} \right), 1 \right) \left(1 + \frac{F}{F_{cr}} \right) H_{sl} (1 + f_{LS}) \quad (10)$$

Where, LAI_{dg} is the mean daily rate of green LAI decrease after anthesis to maturity; S is a soil water stress factor and S_{cr} is the threshold value of S below which soil water begins to affect growth; F is a flooding stress factor and F_{cr} is the threshold value of F below which flooding begins to affect growth; H_{sl} is a heat stress factor; and f_{LS} is a factor accounting for the effect of leaf senescence due to O_3 with leaf age. f_{LS} is calculated as

$$f_{LS} = \left\{ \begin{array}{ll} 1; & \text{if } t_{1,a} \leq t_{1,em} + t_{1,ep} \\ f_{o3,l}; & \text{if } t_{1,em} + t_{1,ep} < t_{1,a} < t_1 \\ 0; & \text{if } t_{1,a} \geq t_1 \end{array} \right\} \quad (11)$$

Where, $t_{l,a}$ is the age of the leaf ($^{\circ}\text{C d}$), $t_{l,em}$ is the thermal time-interval ($^{\circ}\text{C d}$) for the emerging leaf and t_l is the thermal time-interval for the lifespan ($^{\circ}\text{C d}$) of a leaf. t_l comprises the thermal time-intervals of the emerging leaf ($t_{l,em}$) and the mature leaf. And the later comprises the thermal time during which the leaf is fully expanded ($t_{l,ep}$) and during which the leaf is senescing. The factor $f_{o3,l}$ is calculated as a function of accumulated O_3 uptake and an empirically determined coefficient (γ_3):

$$f_{o3,l} = \max(0, \gamma_3 \int_0^{t=t_l} \text{O}_{3,\text{up}} dt) \quad (12)$$

Where, the coefficient γ_3 describes the reduction in lifetime of a mature leaf per unit accumulated O_3 uptake, with $\gamma_3 = 0.1 (\mu\text{mol m}^{-2})^{-1}$ in this study.

The model is run in daily steps, except for the photosynthesis module which is simulated hourly. Daily temperature and solar radiation data are temporally downscaled to hourly data with the method developed in Cesaraccio (2001) and Yang et al (2006). Nitrogen is assumed to be non-limiting; however, water is limiting. According to the general agronomic management practices in the region, we assume no irrigation for wheat in Jiangsu, Anhui and Hubei; however, in Hebei, Henan, Shandong, Shanxi and Shaanxi, irrigation with 50 mm of water is conducted three times around jointing, heading and grain filling stages, respectively.

2.3. Data for model calibration, validation and spatial simulations

O_3 -FACE experiment data, together with hourly weather and $[\text{O}_3]$ data, for model calibration and validation were from Feng et al (2011) and Zhu et al (2011). The experiment was conducted in Xiaoji ($119^{\circ}42'\text{E}$, $32^{\circ}35'\text{N}$), Jiangdu, Jiangsu Province, China (Fig.1). Four modern cultivars of winter wheat (*Triticum aestivum* L.) were

grown under elevated $[O_3]$ (a mean 25% enhancement above the ambient $[O_3]$, 45.7 ppb) in fully open-air field conditions in China for three consecutive growth seasons during 2007–2009. The four cultivars were Yannong 19 (strong-gluten wheat, hereafter Y19), Yangmai 16 (medium-gluten wheat, hereafter Y16), Yangmai 15 (weak-gluten wheat, hereafter Y15) and Yangfumai 2 (weak-gluten wheat, hereafter Y2). Grain yield was determined for all plants from a 2-m² patch in the middle of each subplot. Grain yield components in each subplot were determined at crop maturity, including the number of ears per square meter, the number of grains per ear and 1000-grain mass (Zhu et al., 2011). Gas exchange and fluorescence were measured. Leaf photosynthetic rate (A) vs. intercellular CO_2 concentration (C_i) and A vs. photosynthetic photon flux density (PPFD) curves were also measured for each of two cultivars (Y16 and Y2) (Feng et al., 2011). V_{cmax} and the maximum rate of electron transport (J_{max}) were determined following Farquhar and Sharkey (1982).

For model simulation at $0.5^\circ \times 0.5^\circ$ resolution, daily weather data on maximum temperature, minimum temperature, precipitation, sunshine duration, wind speed and relative humidity at $0.5^\circ \times 0.5^\circ$ resolution for 1996–2005 were interpolated from the measurements from 600 Chinese national meteorological stations using a thin-plate spline method (Yuan et al., 2015). Hourly $[O_3]$ in 2000 and 2020 was simulated by a high-resolution (40 km $\times$ 40 km) global–regional chemical transport model (CTM) system coupled with the Regional Emission inventory in Asia (REAS) (Ohara et al., 2007), as used in Tang *et al* (2013). The CTM system (WRF/Chem-CHASER) was developed to simulate surface $[O_3]$ over Asia, which were consistent with the observations at 251 sites in Japan (Takigawa *et al.*, 2007) and Mount Tai in China (Takigawa et al., 2009). REAS had three scenarios for emission control in China: REF

(reference case), PSC (policy success case) and PFC (policy failure case). The pessimistic scenario of PFC was used here because it was mostly consistent with the trends in Chinese anthropogenic emissions so far (Wang et al., 2011; Zhang et al., 2012). For years 2000 and 2020, each [O₃] simulation was integrated for January–December after a spin-up calculation for one month. The calculated [O₃] was recorded every hour. To account for the vertical [O₃] gradient near the ground, the [O₃] at the reference height (ca. 25 m) was converted to that at canopy height (1 m) following Oue et al (2009). Hourly [O₃] in 2000 and 2020 were used to represent the O₃ conditions for 1996–2005 (i.e. 2000s) and 2016–2025 (i.e. 2020s) in this study.

To develop climate scenarios for 2020s, two global climate models (GCMs), HadGEM2-ES and MIROC-ESM-CHEM, driven by the high-concentration scenario Representative Concentration Pathway 8.5 (RCP 8.5), were selected to understand the worst cases. The data were spatially interpolated and bias-corrected (Weedon et al., 2011; Hempel et al., 2013). Following Tao et al (2003), for each 0.5° × 0.5° grid and each month, the absolute changes for maximum and minimum temperatures, and the relative changes for other climate variables including precipitation, solar radiation, wind speed and vapor pressure, between the GCMs simulated monthly mean for the 2020s and the 2000s were first calculated. Then, climate scenarios for the 2020s were constructed by modifying observed daily weather data for the 2000s with the calculated monthly changes at each grid based on the GCM simulations. The observed annual mean atmospheric [CO₂] for 1996–2005 was 362–380 ppm, and the projection for the 2020s under RCP 8.5 emission scenario was 404–431 ppm.

Wheat sowing dates during 1996–2005 for each grid were from hundreds of Chinese agro-meteorological experiment stations (Tao et al., 2012), and were spatially

interpolated into each $0.5^{\circ} \times 0.5^{\circ}$ grid. Soil texture and hydrological properties data were based on the FAO soil dataset (FAO, 1991). Yearly provincial-level data on wheat yield were obtained from the statistical yearbook of each province.

2.4. Model simulation experiments to determine the interactive effects of climate change, CO₂ and O₃ on crop growth and productivity

The validated MCWLA-Wheat model was applied to simulate the interactive effects of climate change, elevated [CO₂] and rising [O₃] on wheat growth and productivity in each of the eight provinces for 1996–2005 (i.e. 2000s) and 2016–2025 (i.e. 2020s), respectively. We conducted model simulation experiments to investigate the interactive effects of climate change, elevated [CO₂] and rising [O₃] on wheat growth and productivity in 2020s using two representative future climate scenarios, as well as to disentangle the relative effects of climate change, elevated [CO₂] and rising [O₃] on wheat growth and productivity in a setting with the interactions between them.

As the model simulation experiment protocol (Table 1), model simulation experiment 1 (E1) investigated crop growth and productivity under climate and CO₂ conditions in the 2000s without O₃. Model simulation experiment 2 (E2) investigated crop growth and productivity under climate, O₃ and CO₂ conditions in 2000s. Model simulation experiment 3 (E3) investigated crop growth and productivity under O₃ condition in the 2020s, with climate and CO₂ conditions in the 2000s. Model simulation experiment 4 (E4) investigated crop growth and productivity under climate conditions in the 2020s, with O₃ and CO₂ conditions in the 2000s. Model simulation experiment 5 (E5) investigated crop growth and productivity under climate and CO₂ condition in the 2020s, with O₃ condition in the 2000s. Model simulation experiment 6 (E6) investigated crop growth and productivity under climate and O₃ conditions in

the 2020s, with CO₂ condition in the 2000s. Model simulation experiment 7 (E7) investigated crop growth and productivity under climate, O₃ and CO₂ conditions in the 2020s. Therefore, the effect of O₃ in the 2000s on crop growth and productivity were derived by comparing E2 and E1. The effects of O₃ in the 2020s on crop growth and productivity without accounting for elevated CO₂ were derived by comparing E3 and E1. To disentangle the roles of climate change, CO₂ and O₃ in affecting crop productivity, the effect of climate change in the 2020s on crop growth and productivity was derived by comparing E4 and E2. Correspondingly, the effect of CO₂ in the 2020s on crop growth and productivity was derived by comparing E7 and E6; and the effects of O₃ by comparing E7 and E5. The combined effects of climate change and CO₂ on crop growth and productivity in 2020s were derived by comparing E5 and E2. Correspondingly, the combined effects of climate change and O₃ were derived by comparing E6 and E2; the combined effects of CO₂ and O₃ by comparing E7 and E4; the combined effects of climate change, CO₂ and O₃ in the 2020s by comparing E7 and E2.

Table 1 Model simulation experiments protocol to investigate the interactive effects of climate change, CO₂ and O₃ on wheat growth and productivity in the 2020s

Experiment No.	Climate 2000s	Climate 2020s	Without O ₃	2000s_ O ₃	2020s_ O ₃	2000s_ CO ₂	2020s_ CO ₂
E1	√		√			√	
E2	√			√		√	
E3	√				√	√	
E4		√		√		√	
E5		√		√			√
E6		√			√	√	
E7		√			√		√

3. Results

3.1. Calibration and validation of MCWLA-Wheat model in simulating O_3 effect on wheat growth and productivity

After parameterization, the MCWLA-Wheat model is able to simulate wheat development, growth and yield under ambient and elevated $[O_3]$ fairly well for four cultivars in the experiment years of 2007, 2008 and 2009 at the experimental site, in terms of anthesis and maturity date (Fig. S1), LAI (Fig. S2), yield (Fig. S3), the maximum carboxylation efficiency (A_{cmax}) and g_{sc} (Fig. S4). For each of the eight provinces in the study region, the model is adapted and run for 1996–2005 at each $0.5^\circ \times 0.5^\circ$ grid with wheat cultivation across the province. For each grid, annual mean $[CO_2]$ and daily weather data of maximum temperature, minimum temperature, precipitation, solar radiation, wind speed and vapor pressure for 1996–2005, together with hourly $[O_3]$ data in 2000, are input to the model. The sowing area-weighted mean of simulated yields across the grids in a province agree fairly well with reported yields for provinces by the census bureau (Fig. S5). For each of the eight provinces, the root mean square error between the simulated and reported wheat yields is less than 17%.

3.2. Effects of climate change, elevated CO_2 and rising O_3 on wheat growth and productivity, singly and in combination

AOT40 (daytime 9:00–16:00 from 1 March to 31 May) is projected to increase generally from 0.3–6.0 ppm h in 2000 to 1.8–14.8 ppm h in 2020 across the study region (Fig. S6), with the largest increases in the southern and southeastern parts. Atmospheric $[CO_2]$ is projected to increase on average from 370.8 ppm in the 2000s to 417.5 ppm in the 2020s under RCP 8.5. Under the climate and CO_2 conditions in the 2000s (Fig. S7), wheat productivity loss due to O_3 effects is estimated to be 1.1–13.3% in the 2000s and 6.5–21.8% in the 2020s, across the study region (Fig. 2). The

spatial pattern is largely ascribed to local $[O_3]$ (Fig. S6), as well as local climate and soil moisture conditions that affect g_{sc} and O_3 uptake. With the climate condition in the 2000s but O_3 and CO_2 conditions in the 2020s, wheat productivity loss is estimated to be 1.7–18.0%, across the study region (Fig. 2), which is 2.9–7.7% less than the effect of single O_3 across the study region. Nevertheless, O_3 damage may outweigh CO_2 benefit to wheat productivity in most of the region (Fig. 2).

The projections under the HadGEM2-ES and MIROC-ESM-CHEM climate scenarios (the values of the latter model in parentheses), during the wheat growing period (1 October to 31 May) follow: maximum temperature to change by -0.32 to 1.06°C (0.54 to 1.68°C), minimum temperature to increase by 0.22 to 1.99°C (0.66 to 1.45°C), solar radiation to change by -4.76 to -0.53% (-0.74 to 2.87%) and precipitation to change by -6.57 to 45.26% (-15.67 to 9.2%) in the 2020s relative to the 2000s (Figs. S8, S9). When the roles of climate change, CO_2 and O_3 are disentangled, under the HadGEM2-ES climate scenario, climate change is projected to change wheat productivity by -13.0 to 5.3% in the 2020s across the study region, relative to the 2000s (Fig. 3a), mainly owing to projected decreases in solar radiation and maximum temperature (Fig. S8). In contrast, under the MIROC-ESM-CHEM climate scenario, wheat productivity is projected to change by -5.3 to 16.0% (Fig. 4a) mainly owing to projected increases in temperature, precipitation and solar radiation (Fig. S9). Rising $[O_3]$ in the 2020s is projected to reduce wheat productivity by 2.8–11.0% and 3.1–11.7% under the HadGEM2-ES (Fig. 3b) and MIROC-ESM-CHEM (Fig. 4b) climate scenarios, respectively, relative to the 2000s. Elevated $[CO_2]$ in the 2020s is projected to increase wheat productivity by 2.8–8.6% and 3.0–9.0% under the HadGEM2-ES (Fig. 3c) and MIROC-ESM-CHEM (Fig. 4c) climate scenarios,

respectively. The combined effects of climate change and O₃, climate change and CO₂, and CO₂ and O₃ are projected to change wheat productivity by -20.0 to -0.1%, -9.3 to 12.0%, and -7.9 to 5.3% under HadGEM2-ES (Fig. S10) and by -13.0 to 11.8%, -1.1 to 23.0%, and -7.6 to 4.6% under MIROC-ESM-CHEM climate scenario, respectively, in the 2020s (Fig. S10). As a result, the combined effects of climate change, CO₂ and O₃ are projected to change wheat productivity by -16.8 to 6.8% and -9.1 to 18.1% under the HadGEM2-ES (Fig. 3d) and MIROC-ESM-CHEM (Fig. 4d) climate scenarios, respectively, relative to the 2000s. Across the study region, the effects of climate change, CO₂ and O₃ are of the same order of magnitude on average; the effects of CO₂ and O₃ are generally consistent, although the effects of climate change are quite different under the two different scenarios (Fig. 5). The combined effects of climate change and O₃, CO₂ and O₃, and climate change, CO₂ and O₃ may modify the effect of single O₃ on wheat productivity on average by -5.0%, 4.6%, and -0.2%, respectively, in the 2020s, under HadGEM2-ES climate scenario (Fig. 5). The corresponding value is 3.5%, 5.2%, and 8.6% under MIROC-ESM-CHEM climate scenario (Fig. 5). O₃ damage may outweigh CO₂ benefit to wheat productivity in most of the region under both climate scenarios (Fig. 5, Fig. S10).

3.3. Effects of climate change, CO₂ and O₃, singly and in combination, on wheat productivity by province

By province, under the climate and CO₂ conditions in the 2000s, O₃ is estimated to reduce wheat productivity from 1.0% in Shaanxi to 5.9% in Jiangsu in the 2000s and from 4.0% in Shaanxi to 10.9% in Anhui in the 2020s (Fig. 6). Under the HadGEM2-ES scenario, from the 2000s to 2020s, climate change is projected to reduce wheat yield on average from 0.8% in Shanxi to 9.2% in Hubei; O₃ to reduce yield from 2.0%

in Hebei to 5.2% in Anhui; CO₂ to increase yield from 3.0% in Hubei to 7.7% in Hebei; and interactive effects of climate change, CO₂ and O₃ to change yield from -10.6% in Hubei to 4.9% in Hebei. Under the MIROC-ESM-CHEM scenario, from the 2000s to 2020s, climate change is projected to change wheat yield on average from -0.2% in Shannxi Province to 9.4% in Shandong; O₃ to reduce yield from 2.5% in Hebei to 5.7% in Anhui; CO₂ to increase yield from 3.4% in Hubei to 7.8% in Hebei; and interactive effects of climate change, CO₂ and O₃ to change yield from -1.1% in Hubei to 12.0% in Hebei (Fig. 6).

4. Discussion

4.1. Spatial patterns of the effects of climate change, elevated [CO₂] and rising [O₃] on wheat productivity

The effects of climate change, elevated [CO₂] and rising [O₃] on wheat productivity have spatially explicit patterns (Figs. 3, 4), which can be well explained by the projected climate, [CO₂] and [O₃] in the 2020s. Wheat productivity may benefit from climate change in areas where temperature and precipitation are relatively low, such as the northern parts (Figs. 7a, e, Figs. S7, S8, S9). By contrast, climate change may have negative effects on wheat productivity in areas where temperature and precipitation are relatively high, such as the southern parts (Figs. 7a, e, Figs. S7, S8, S9). These results are supported by previous studies based on long-term trial data (Tao et al., 2014) and controlled experiments (Fang et al., 2015). The effects of O₃ vary with temperature, availability of water and local [O₃], and are large in areas with high temperature, precipitation and local [O₃] such as the southern parts (Figs. 7b, f, Figs. S7, S8, S9). The reason is that the effect of O₃ on photosynthesis or biomass growth is less for stress than non-stress conditions (Fiscus et al., 2005; Feng et al., 2008).

Elevated [CO₂] and/or drought stress lead to a reduction in stomatal conductance and consequently counteract the adverse effect of elevated [O₃] on photosynthesis (Vandermeiren et al., 2002; Morgan et al., 2006; Wittig et al., 2007). The effects of CO₂ vary with temperature, availability of water and solar radiation, and are large in areas with low temperature and precipitation and high solar radiation, such as the northern parts (Figs. 7c, g). The results are supported by some previous controlled experiments (Ainsworth et al., 2008; Kimball et al., 2016), which indicated that elevated [CO₂] (550 ppm in comparison with an ambient concentration of about 353 ppm in 1990) increased yields of C3 crops on average by about 19%, with yields increasing more under dry than wet conditions. The combined effects of climate change, elevated [CO₂] and rising [O₃] on wheat productivity are suggested by the model to be dominated by climate change but with substantial modifications from the effects of CO₂ and O₃ (Figs. 7d, h).

Climate change not only affects crop growth and yield directly, but also affects crop growth and productivity indirectly by modifying the roles of CO₂ and O₃. The HadGEM2-ES and MIROC-ESM-CHEM climate scenarios result in different climate conditions and consequently have different effects on crop productivity. Decreases in solar radiation and maximum temperature were projected in a large part of the region by HadGEM2-ES climate scenarios (Fig. S8), which would reduce crop growth and photosynthesis and consequently decrease crop productivity in this region (Tao and Zhang, 2013; Tao et al., 2014). By contrast, increases in solar radiation and temperature were projected in a large part of the region by MIROC-ESM-CHEM climate scenarios (Fig. S9), which would increase crop productivity in this region (Tao and Zhang, 2013; Tao et al., 2014).

4.2. Comparisons with previous studies

The magnitude of estimated O₃ effect on wheat productivity at a regional scale is generally comparable with previous field experiments and estimates (Van Dingenen et al., 2009; Tang et al., 2013; Avnery et al., 2011a, b). For example, previous field experiments using open top chamber showed that non-filtered ambient air, 50 and 100 ppb O₃ induced wheat yield loss by -4.7%, 10.5% and 58.6%, respectively, at Gucheng (32°16'N, 111°39'E) in China, relative to charcoal-filtered air (Feng et al., 2003); wheat yields were reduced by 8.5–58% and 40–73%, respectively, with yearly O₃ concentration of 75 and 100 ppb, at Jiaxing (31°53'N, 121°18'E) in China (Wang et al., 2012). At regional and global scale, previous studies using empirical exposure-based and/or flux-based approaches suggested that O₃ could reduce wheat productivity by 6.4–14.9% in 2000, with a further reduction of 8.1–9.4% in 2020, in China (Tang et al., 2013). Global estimates of yield losses due to elevated [O₃] in wheat were 3.9–15% in 2000 (Avnery et al., 2011a), with a further reduction of 1.5–10% in 2030 (Avnery et al., 2011b). Another global estimate of yield losses due to rising [O₃] for wheat were 7.0–12% in 2000, and a further reduction of 2–6% in 2030 relative to 2000 (Van Dingenen et al., 2009). However, the spatial patterns of O₃ effect produced here are very different from those using the empirical exposure-based and the flux-based approaches (e.g., Van Dingenen et al., 2009; Tang et al., 2013; Avnery et al., 2011a, b). This inconsistency can be likely related to the interactions between crop growth, climate variables, soil and agronomic management (Simpson et al., 2007; Karlsson et al., 2009; Anav et al., 2016). With the robust photosynthesis and stomatal conductance coupling mechanisms and the eco-physiological mechanistic model approaches, in this study the changes in stomatal conductance with changes in

photosynthesis depend on [CO₂], surface air temperature, vapor pressure deficit, and soil water conditions. Furthermore, this study accounts for the interactions between crop development, environment and agronomic management, estimates the combined effects of climate change, CO₂ and O₃ on crop productivity, which is particularly important when predicting global change effects on crop productivity for future (Fiscus et al., 2005).

4.3. Implications of the study to global change impact studies, O₃ regulation and climate adaptation

It is a better and more relevant approach to assess land surface-atmospheric feedbacks using well validated eco-physiological mechanistic models (Anav et al., 2016), although it is challenging and need to be further developed. Recently, some high quality controlled experiment data such as CO₂-FACE and infrared heating with a wide range of sowing dates have been used to test and improve crop models (including the MCWLA family model) in simulating the effects of elevated [CO₂] and climate warming on crop productivity (Asseng et al., 2015; Durand et al., 2016). However, the studies using the O₃-FACE experiment data to test and improve crop models have been scarce so far because the effect of O₃ is not formulated into the commonly used crop models as well as the effect of CO₂. This is the reason why the effect assessment of O₃ is less developed than that of climate change and CO₂. The model takes into account two major impact mechanisms of O₃ as suggested by O₃-FACE experiment, one reversible effect on photosynthesis and one non-reversible effect on green LAI and thus indirectly on photosynthesis. The direct effects of O₃ on photosynthesis can be larger for crop productivity (Figs. S3, S5). In addition, with a well validated crop model, many climate change impact studies conclude that

although global crop yields would be reduced in future due to increased temperature and decreased soil moisture, the direct fertilization effect of rising [CO₂] will offset these losses (Porter et al., 2014). Our study indicates that if the role of O₃ is taken into account, the projected global change impacts on crop productivity could be significantly different in some areas with negative net effects of global change. Therefore, the multiple global change factors and their interactions should be incorporated into eco-physiological mechanistic models and should be taken into account simultaneously in global change impact studies (Ren et al., 2012). To further improve the modeling system, the characteristics of agronomic management such as heterogeneous applications of nitrogen, irrigation and crop cultivars across the study region should be better represented in the simulations because the interactions between climate, CO₂ and O₃ are closely dependent on soil nitrogen and water conditions, and crop cultivars have different resilience to rising [O₃] and climate change. In addition, more climate change scenarios should be used to better represent the uncertainties in future climate scenarios.

Previous studies indicated that wheat yield increased on average by 1.3–2.3% per year in this region due to varieties renewal and advances in technology and management (Tao et al., 2014). Therefore, the yield losses from climate change and O₃ are large enough to offset a notable proportion of increase from varieties renewal and advances in technology and management in some areas. Our results warrant the necessity of mitigation of O₃ precursors and greenhouse gas such as nitrogen oxides, carbon monoxide, methane, and nonmethane volatile organic compounds, as well as adaptation to ongoing climate change and air pollution by selecting climate resilient and O₃ resistant crop cultivars. The derived spatially explicit patterns for the

interactive effects of climate change, elevated [CO₂] and rising [O₃] on crop productivity can be used to prioritize O₃ regulation and climate adaptation in different areas.

5. Conclusions

In this study, we incorporate the interactions between climate change, CO₂ and O₃ into an eco-physiological mechanistic model based on three years of O₃-FACE experiments. We then investigate the effects of climate change, elevated [CO₂] and rising [O₃] on wheat growth and productivity in eastern China in the 2000s and the 2020s under two climate change scenarios, singly and in combination. Our findings indicate that O₃ damage may outweigh CO₂ benefit to wheat productivity, which cast doubt on the potential of CO₂ fertilization effects in offsetting possible negative effects of climate change on crop productivity as suggested by many previous climate impact studies. Our results indicate that in some areas the yield loss from climate change and O₃ are large enough to offset a notable proportion of increase from technological and management advances. The study demonstrate a better and more relevant method for assessing the interactive effects of climate change, CO₂ and O₃ on crop growth and productivity, highlighting the importance of accounting for multiple global change factors simultaneously in impact studies. Moreover, the resultant spatially explicit patterns for the interactive effects of climate change, elevated [CO₂] and rising [O₃] on crop productivity provide important evidence for prioritizing O₃ regulation and climate adaptation in different areas.

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Figure 1 Wheat cultivation fraction and the study region including eight provinces in China, as well as the location of Xiaoji where the O₃-FACE experiment was conducted.

Figure 2 Estimated wheat yield change owing to O₃ effects in the 2000s (upper) and the 2020s (middle) with climate and CO₂ conditions of the 2000s, and in the 2020s (lower) with climate condition in the 2000s but CO₂ condition in the 2020s.

Figure 3 Estimated changes in wheat yield owing to climate change (a), O₃ (b), CO₂ (c) and their combinations (d) in the 2020s accounting for interactions between climate, O₃ and CO₂ under the HadGEM2-ES climate scenario, relative to 2000.

Figure 4 Estimated changes in wheat yield owing to climate change (a), O₃ (b), CO₂ (c) and their combinations (d) in the 2020s accounting for interactions between climate, O₃ and CO₂ under the MIROC-ESM-CHEM climate scenario, relative to 2000.

Figure 5 Estimated wheat yield change owing to climate change (HD CC, MI CC), O₃ (HD O₃, MI O₃), CO₂ (HD CO₂, MI CO₂), the interaction between climate change and O₃ (HD CCxO₃, MI CCxO₃), the interaction between climate change and CO₂ (HD CCxCO₂, MI CCxCO₂), the interaction between O₃ and CO₂ (HD O₃xCO₂, MI O₃xCO₂) and the interaction between climate change, CO₂ and O₃ (HD CCxO₃xCO₂, MI CCxO₃xCO₂) in the 2020s under the HadGEM2-ES (HD) and MIROC-ESM-CHEM (MI) climate scenarios, relative to 2000s, across the study region. The error bars represent the standard deviation of the estimates across the grids in the study region.

Figure 6 Estimated wheat yield change owing to O₃ in the 2000s (2000s O₃) and 2020s (2020s O₃) under climate and CO₂ conditions of the 2000s; as well as because of climate change (2020s HD CC and 2020s MI CC), O₃ (2020s HD O₃ and 2020s MI O₃), CO₂ (2020s HD CO₂ and 2020s MI CO₂) and their combinations (2020s HD CCxO₃xCO₂ and 2020s MI CCxO₃xCO₂) in the 2020s under the HadGEM2-ES (HD) and the MIROC-ESM-CHEM (MI) climate scenarios, relative to 2000s for each of the eight provinces in the study region. The error bars represent the standard deviation of the estimates across the grids in a province.

Figure 7 Effects of climate change (a, e), O₃ (b, f), CO₂ (c, g) and their combinations (d, h) on wheat productivity in relation to mean temperature and precipitation from 1 March to 31 May during the 2020s, under the HadGEM2-ES (a, b, c and d) and MIROC-ESM-CHEM (e, f, g and h) climate scenarios.