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Worsened Ozone Pollution Exacerbates the Loss of Agricultural Production in China

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Key Points:

- Increased O_3 concentrations pose a non-negligible threat on food security in China
- O_3 pollution caused 4.0% yield loss of the four agricultural crops during 2013–2018
- Improved O_3 air quality due to future control measures will decrease crop yield loss

Supporting Information:

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

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Abstract China has been experiencing severe ozone (O_3) pollution, and the high concentration of O_3 exposure can damage crop production, which will threaten the national food security. To better estimate the impact of O_3 on crop production loss (CPL), we collect O_3 data from CNEMC (China National Environmental Monitoring Centre) and CMIP6 (Coupled Model Intercomparison Project Phase 6) models to quantify O_3-induced production losses in the four main crops (i.e., wheat, rice, maize, and soybean) during the historical (2013–2018) and future (2019–2099) periods. Results confirm that the impacts of O_3 damage on CPLs become more and more serious during 2013–2018 in China, with the 6-year mean losses of 12.2 Mt (8.5%) for wheat, 8.4 Mt (3.8%) of rice, 4.3 Mt (1.6%) of maize, and 0.7 Mt (4.8%) of soybean. The worsened O_3 pollution under SSP3-7.0 scenario during the late-century will cause 283.6% (170.3%, 479.4%, 168.0%) increase in wheat (rice, maize, soybean) production losses relative to that in 2018, while the improved O_3 air quality under SSP1-2.6 scenario can decrease 73.8% (69.3%, 80.8%, 75.5%) wheat (rice, maize, soybean) yield losses during the late-century relative to 2018. China has the largest population and food consumption worldwide, and the persistent O_3 deterioration does have exacerbated the loss of agricultural productions. Therefore, stricter control measures are urgently needed to improve O_3 air quality for ensuring national and even per capita food security in future.

Plain Language Summary As a major air pollutant, ozone (O_3) can not only do harm to public health, but also damage the ecosystem. During recent years, the O_3 pollution in China has become more and more serious, which may exacerbate the loss of agricultural production and finally threaten national food security. In this study, we quantified the yield losses of major crops (wheat, rice, maize, and soybean) by using different O_3-related metrics, and found that O_3 pollution did cause 4.0% agricultural yield loss during 2013–2018 in China through multi-metrics ensemble mean. This threat should be emphasized especially in major grain growing regions, such as Henan and Shandong provinces. We future explored the pathways of crop yield loss contributed by ozone damage under different future development scenarios, emphasizing the improved O_3 air quality due to future control measures will decrease crop yield loss.

1. Introduction

With the rapid urbanization and economic growth in China, air pollution has become a serious environmental problem (Fan et al., 2020), leading to a considerable health burden and economic losses (Rohde & Muller, 2015; Xing et al., 2016; Xu et al., 2022; Yang et al., 2013). Therefore, a series of strict emission strategies has been implemented by the Clean Air Action of the Chinese government since 2013 to improve air quality (State Council of the People's Republic of China, 2013, 2018). From 2013 to 2018, the national concentrations of particles in the atmosphere with an aerodynamic equivalent diameter of 2.5 microns or less ($PM_{2.5}$) were shown a significant downward trend with an annual decrease around 7% compared with measurements in 2013 (Fan et al., 2020; Wang et al., 2020; Xue et al., 2021). However, the ozone (O_3) concentrations increased at a rate of 2.5 $\mu g \cdot m^{-3} \cdot yr^{-1}$ during 2013–2020, and it has been becoming one of the most important air pollutants in China (Chen et al., 2020; Li et al., 2023; Lu et al., 2018; Wang et al., 2020; Wei et al., 2022). Surface O_3 is a short-lived trace gas produced by photochemical reactions involving carbon monoxide (CO) and volatile organic compounds

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(VOCs) in the presence of nitrogen oxides ($NO_X = NO + NO_2$) and sunlight (Cooper et al., 2014; Simon et al., 2015), which can pose a threat to public health (Liu et al., 2021; Turner et al., 2016; Wang et al., 2021). O_3 is also a kind of phytotoxic air pollutant that can infiltrate leaf tissues via stomata (Emberson, 2020), triggering reactive oxygen species (ROS) overproduction (Ueda et al., 2013; Vainonen & Kangasjärvi, 2015). Excessive ROS overwhelms antioxidant defenses (Tausz et al., 2007; Wieser et al., 2002), accelerating damage of the photosynthetic system through energy-intensive detoxification processes that impair photosynthesis and metabolism (Feng et al., 2008; Wittig et al., 2009), and even leads to programmed cell death. Concurrent stomatal closure from ROS accumulation restricts CO_2 assimilation and transpiration, collectively diminishing crop productivity and threatening global food security (Agathokleous et al., 2020; Dumont et al., 2014; Emberson, 2020; Feng et al., 2022; Tian et al., 2016; Unger et al., 2020).

To map the risks of crops caused by O_3 pollution, previous studies have established many metrics that qualitatively reflect the relationship between O_3 concentration and crop yield damage, for example, M7/M12 (averaged hourly O_3 during daytime), AOT40 (accumulated hourly exposure O_3 above 40 ppb), W126 (weighted cumulative hourly O_3), and SUM06 (accumulated hourly O_3 above 60 ppb) though free air concentration enrichment or open top chamber (Feng et al., 2018, 2022; Nussbaum et al., 1995; Zheng et al., 1998). Mills et al. (2018) assessed the reduction of global wheat due to the damage of O_3 pollution by using AOT40 and M7. Their results showed that the mean percentage yield losses over wheat growing areas were 13.8% and 13.4% for AOT40 and M7, respectively. As the most populous country in the world, food security is a major issue in China, which is crucial for global food supply. Some studies have researched to establish dose-response relationships between O_3 pollution and crop yield loss derived from M7/M12, AOT40, SUM06 and W126 for major crops in China (Aunan et al., 2000; Feng et al., 2012; Wang & Mauzerall, 2004; Zhu et al., 2011). According to the results of these dose-response relationships, China's yield loss due to O_3 pollution were severe with the reduction in wheat of 8.7–73 million metric ton per year (Feng et al., 2022; Lin et al., 2018; Y. Wang et al., 2022; Zhao et al., 2020). Although M7/M12, AOT40, W126 and SUM06 related dose-response relationships can quantitatively evaluate the damage of O_3 to crops, the simulation of crop yield losses based on these different metrics varies greatly, and the large uncertainty is worthy of further exploration.

Future climate change may deteriorate O_3 air quality (Gao et al., 2013; Guo et al., 2023; Li et al., 2019a, 2019b, 2023), which will threaten per capita food security, especially in China (Tai et al., 2014). To quantify future changes in yield loss due to worsened O_3, numerical models can provide necessary information. The Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) for Fourth Assessment Report (AR4) provides scenario support for assessing the modeling of air pollution (Wang et al., 2013; Zhu et al., 2017). The Coupled Model Intercomparison Project Phase 5 (CMIP5) developed the Representative Concentration Pathways (RCPs) emissions scenarios which also provided future air quality assessments to support IPCC AR5 (Zhu & Liao, 2016). Recently, the Climate and Earth System Models has updated the assessment of air quality in the Coupled Model Intercomparison Project Phase 6 (CMIP6) for IPCC AR6, which generates new emission scenarios driven by different socio-economic models named Shared Socioeconomic Pathways (SSPs) to replace RCPs (Gidden et al., 2019; Zhou et al., 2019). The future changes in O_3 under different SSPs will affect the assessment of public health burden (Chen et al., 2023; P. Wang et al., 2022) and crop damage. However, there is still a lack of research on quantifying the future crop yield loss in China due to O_3 exposure based on CMIP6 simulations.

To explore the historical and the future crop yield loss due to O_3 stress in China, observed O_3 data during 2013–2018 and predicted O_3 concentrations under different SSPs scenarios from 2019 to 2099 are analyzed. The four popular metrics (i.e., M7/M12, AOT40, SUM06, and W126) are all selected with the aim to quantify the potential biases in crop yield loss by using different metrics and to demonstrate the serious influence of worsened O_3 pollution on food security through multi-metric ensemble mean. We discuss the damage on four main types of human's foodstuffs (i.e., wheat, including winter wheat and spring wheat; rice, including single crop rice, double early rice and double late rice; maize, including north maize and south maize; soybean), and select winter wheat as an example in the main text for detailed analysis. Section 2 presents the data and the method. Section 3 shows the loss of agricultural production due to historical and future O_3 damage. Conclusions and discussions are provided in Section 4.

2. Data and Method

2.1. Ozone Data

The observed hourly O_3 concentrations during the period of 2013–2018 were obtained from China National Environmental Monitoring Centre (CNEMC, http://www.cnemc.cn/). A z-score method was applied to assure the quality of observations. More details about the z-score method can be found in Barrero et al. (2015) and He et al. (2017). Figure S1 in Supporting Information S1 shows the spatial distribution of the monitoring stations, including the Chinese administrative division.

In order to generate gridded O_3 concentrations, we conducted inverse distance weighted interpolation (IDW) on observed hourly data from all stations to the grid with the horizontal resolution of $0.0833° \times 0.0833°$. IDW is a popular method of mapping station data to grid data based on the distance relationship between the grid and the stations (Chen & Liu, 2012; Wang et al., 2014). Comparisons between the new generated hourly gridded and observed concentrations are shown in Figure S2 in Supporting Information S1. The average coefficient of determination (R^2) during 2013–2018 is 0.92, indicating that the gridded concentrations can reproduce the observations robustly.

Figure S3 shows the spatial distribution of annual mean grid O_3 concentrations during 2013–2018. The O_3 concentrations increased from 44.7 $\mu g \cdot m^{-3}$ in 2013 to 60.0 $\mu g \cdot m^{-3}$ in 2018 with the increase trend of +3.4 $\mu g \cdot m^{-3}\ yr^{-1}$. High levels of O_3 pollution can be found mainly over the crop areas (Figure S4 in Supporting Information S1) which may lead to large reductions in crop yields.

Hourly O_3 concentrations during 2018–2099 are obtained from future projection of Scenario Model Intercomparison Project (ScenarioMIP) in CMIP6 (https://esgf.nci.org.au/projects/cmip6-nci/) (Simulation results in 2018 are used to compare those during 2019–2099 for quantifying future variations). The Tier-1 experiment (Level 1 core experiment in ScenarioMIP) provides four combined scenarios of SSPs (shared socioeconomic pathways) and radiative forcing (Zhang et al., 2019), that is, SSP1-2.6 (Combination of low social vulnerability and low radiative forcing), SSP2-4.5 (Combination of medium social vulnerability and medium radiative forcing), SSP3-7.0 (Combination of high social vulnerability and relatively high radiative forcing) and SSP5-8.5 (Combination of high social vulnerability and high radiative forcing). We adopted simulations from four global climate models CESM2-WACCM, GFDL-ESM4, MPI-ESM-1-2-HAM, and EC-Earth3-AerChem (Table S1 in Supporting Information S1), and a nearest neighbor interpolation method was applied to resample the simulated hourly O_3 concentrations to the specified grid (0.0833°) for analyzing the damage of future O_3 to Chinese food security.

2.2. Crop Data

We use a combination of gridded crop production data from Global Agro Ecological Zones (GAEZ, https://gaez.fao.org/) and the annual provincial yield data from China Statistics Yearbook (CSY, https://data.stats.gov.cn) to obtain the gridded crop productions during years 2013–2018. All gridded crop yields in a province are multiplied by a factor which is the proportion of provincial yield data provided by CSY to the sum of gridded crop production data in corresponding provinces provided by GAEZ. The gridded crop production data have the horizontal resolution of 0.0833°, which is consistent with the O_3 concentration data.

The crops we consider in this study include wheat, rice, maize and soybean, and the four crops are further divided into eight subcategories based on their different growth seasons for more accurate assessment of O_3-related crop yield loss. More details about the provincial distribution of the eight subcategories (i.e., winter wheat, spring wheat, single crop rice, double early rice, double late rice, north maize, south maize and soybean) are described in Table S2 in Supporting Information S1, following Li et al. (2022), Lin et al. (2018), and Zhao et al. (2020).

The updated yield distributions of the eight crops averaged over 2013–2018 are shown in Figure S4 in Supporting Information S1. According to Figure S4 in Supporting Information S1, we can find that the concentrated planting areas for the crops are different. The planting of winter wheat is mainly concentrated over Henan and Shandong provinces, while the planting of spring wheat is relatively scattered, with more yield in Xinjiang and Inner Mongolia. Maize is the most high-yielding crop in China, with the north maize mainly in Henan, Shandong, Hebei, and Heilongjiang, and the southern maize mainly in southern China, for example, Sichuan, Jiangsu, and Anhui. Rice is also a major grain crop in China. Single season rice is commonly planted in Heilongjiang, Jiangsu, Anhui, and Hubei. The distributions of double early rice and double late rice are similar, with high yields in

Jiangxi, Hunan, Guangdong, and Guangxi. Soybean is mainly grown in Heilongjiang Province. Overall, the provinces of Henan, Shandong, and Heilongjiang are the main crop producing areas in China.

2.3. Exposure-Response Function Between Ozone Concentration and Crop Production Loss

O_3 can damage plant leaves, leading to a decrease in photosynthetic rate and carbon assimilation capacity, ultimately reducing the accumulation of production (Ren et al., 2007). The higher concentration of O_3, the more loss can be found in crop yields, and the damage of O_3 to crops mainly occurs during the growing seasons (Table S3 in Supporting Information S1), which are 90 days before their maturity periods (Van Dingenen et al., 2009).

In order to quantitatively evaluate the impacts of O_3 on crop yields, we select four widely used metrics including M7/M12 (in unit of ppb), AOT40 (in unit of ppm × h), SUM06 (in unit of ppm × h) and W126 (in unit of ppm × h) (Adams et al., 1989; McGrath et al., 2015; Mills et al., 2007; Nussbaum et al., 1995; Wang & Mauzerall, 2004). M7/M12 is a type of nonlinear Weibull response equation between average O_3 and crop yield, which considers that crops are severely affected by O_3 during daytime photosynthesis (9:00–15:59 for M7 and 8:00–19:59 for M12) (Lesser et al., 1990). Plants have resistance to O_3, and it will have a significant impact when the O_3 concentration exceeds a certain threshold. Therefore, SUM06 (accumulated hourly O_3 above 60 ppb) (Wang & Mauzerall, 2004) and AOT40 (accumulated hourly exposure O_3 above 40 ppb) (Mills et al., 2007) are established to evaluate the damage of O_3 to crops. W126 simulates crop tolerance by assigning different weights to hourly O_3 (weight in the range of 0–1) using the sigmoid function (an S-shaped curve) (Feng & Peng, 2021). Detailed definitions of these metrics are shown as follows:

$$M7/M12 = \frac{1}{n}\sum_{i=1}^{n}[O_3]_i \tag{1}$$

$$\text{AOT40} = \sum_{i=1}^{n}\left([O_3]_i - 0.04\right), \text{when } O_3 \geq 0.04\text{ppm} \tag{2}$$

$$\text{SUM06} = \sum_{i=1}^{n}[O_3]_i, \text{when } O_3 \geq 0.06\text{ppm} \tag{3}$$

$$W126 = \sum_{i=1}^{n}\omega_i[O_3]_i \tag{4}$$

$$\omega_i = 1/\left\{1 + 4403\exp\left(-0.126[O_3]_i\right)\right\} \tag{5}$$

where $[O_3]_i$ means the hourly O_3 concentrations at the ith hour, which are assumed to be 09:00–15:59 for M7, 08:00–19:59 for M12 and AOT40, and 00:00–23:59 for SUM06 and W126 (Wang & Mauzerall, 2004; Y. Wang et al., 2022). n represents the number of hours exposed to O_3 during the growing season of each crop.

Based on these metrics, we can further construct dose-response relationships between O_3 and relative yield loss (RYL) (Table 1), and the crop production loss (CPL) due to O_3 damage can finally be calculated from RYL and the actual crop production (CP) as follows:

$$\text{CPL} = \text{CP} \times \text{RYL}/(1 - \text{RYL}) \tag{6}$$

3. Results

3.1. Historical Winter Wheat Production Loss Due To Ozone Damage

Concentration-based metrics (i.e., M7/M12, AOT40, SUM06, and W126) can be used to qualitatively describe the damaging effect of O_3 on agricultural production. Figure 1 shows the spatial distribution of M7 (Figure 1a), AOT40 (Figure 1b), SUM06 (Figure 1c), and W126 (Figure 1d) averaged over 2013–2018 during the growing season for winter wheat. A good consistency in the distribution of O_3 stress can be found among these metrics, with high values over eastern China and low values over southern China. However, the calculated magnitudes of these metrics are inconsistent, for example, the values of W126 are always higher than that of AOT40 and

Table 1
Does-Response Relationships Between Ozone-Related Metrics and Relative Yield Losses for Each Crop

Crop	Dose-response relationship	Reference
Wheat	$RYL = 1 - \exp\left[-(M7/137)^{2.34}\right]/\exp\left[-(25/137)^{2.34}\right]$ (Only for winter wheat)	Lesser et al. (1990)
	$RYL = 1 - \exp\left[-(M7/186)^{3.2}\right]/\exp\left[-(25/186)^{3.2}\right]$ (Only for spring wheat)	Adams et al. (1989)
	$RYL = 1 - \exp\left[-(\mathrm{SUM06}/52.32)^{2.176}\right]$	Wang and Mauzerall (2004)
	$RYL = 1 - \exp\left[-(W126/51.2)^{1.747}\right]$	Wang and Mauzerall (2004)
	$RYL = 1 + 0.0161 \times \mathrm{AOT40} - 0.99$	Mills et al. (2007)
	$RYL = 0.0228 \times \mathrm{AOT40}$ (Only for winter wheat)	Wang et al. (2012)
	$RYL = 1 - \exp(-0.0255 \times \mathrm{AOT40})$ (Only for winter wheat)	Wang et al. (2012)
Rice	$RYL = 1 - \exp\left[-(M7/202)^{2.47}\right]/\exp\left[-(25/202)^{2.47}\right]$	Adams et al. (1989)
	$RYL = 1 + 0.0039 \times \mathrm{AOT40} - 0.94$	Mills et al. (2007)
	$RYL = 0.009489 \times \mathrm{AOT40}$	Wang et al. (2012)
	$RYL = 1 - \exp(-0.0092AOT40)$	Wang et al. (2012)
Maize	$RYL = 1 - \exp\left[-(M12/124)^{2.83}\right]/\exp\left[-(20/124)^{2.83}\right]$	Lesser et al. (1990)
	$RYL = 1 - \exp\left[-(\mathrm{SUM06}/93.485)^{3.5695}\right]$	Wang and Mauzerall (2004)
	$RYL = 1 - \exp\left[-(W126/93.7)^{3.392}\right]$	Wang and Mauzerall (2004)
	$RYL = 1 + 0.0036 \times \mathrm{AOT40} - 1.02$	Mills et al. (2007)
	$RYL = 1 + 0.0067 \times \mathrm{AOT40} - 1.03$	Singh et al. (2014)
Soybean	$RYL = 1 - \exp\left[-(M12/107)^{1.58}\right]/\exp\left[-(20/107)^{1.58}\right]$	Lesser et al. (1990)
	$RYL = 1 - \exp\left[-(\mathrm{SUM06}/101.505)^{1.452}\right]$	Wang and Mauzerall (2004)
	$RYL = 1 - \exp\left[-(W126/109.75)^{1.2315}\right]$	Wang and Mauzerall (2004)
	$RYL = 1 + 0.0116 \times \mathrm{AOT40} - 1.02$	Mills et al. (2007)
	$RYL = 0.012 \times \mathrm{AOT40}$	Zhang et al. (2017)

SUM06, indicating potential biases in calculated crop production loss by using these metric-related dose-response relationships. Generally, the national mean values of M7, AOT40, SUM06, and W126 averaged over 2013–2018 during the growing season of winter wheat are 30.2 ppb, 3.0 ppm × h, 3.1 ppm × h, and 4.1 ppm × h, respectively.

Crop production loss (CPL) is associated with crop production (CP) and O_3 concentration-based metrics, which means high concentrations of O_3 in areas with high crop yields will lead to large CPL. Figure 2 shows the spatial distribution of annual mean winter wheat production loss due to O_3 damage during the growing season over 2013–2018. From Figure 2 we can find that similar CPLs are calculated among these different metrics (M7, AOT40, SUM06, and W126), with large CPLs over Hebei, Henan, Shandong, Jiangsu and Anhui provinces and small

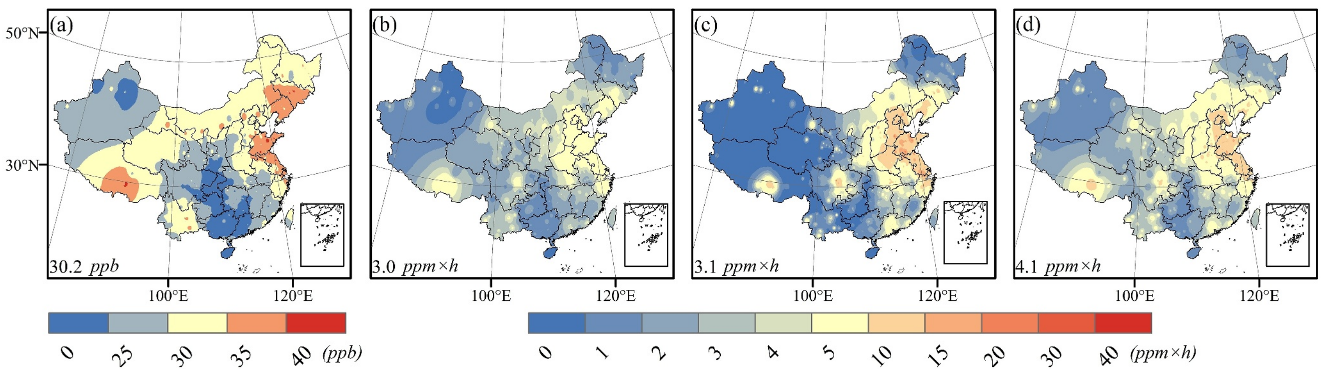

Figure 1. Spatial distribution of O_3 concentration-based metrics averaged over 2013–2018 during the growing season of winter wheat. (a) M7, (b) AOT40, (c) SUM06, and (d) W126. The number in the bottom of each panel represents the national mean value. The unit of M7 (AOT40, SUM06, and W126) is ppb (ppm × h).

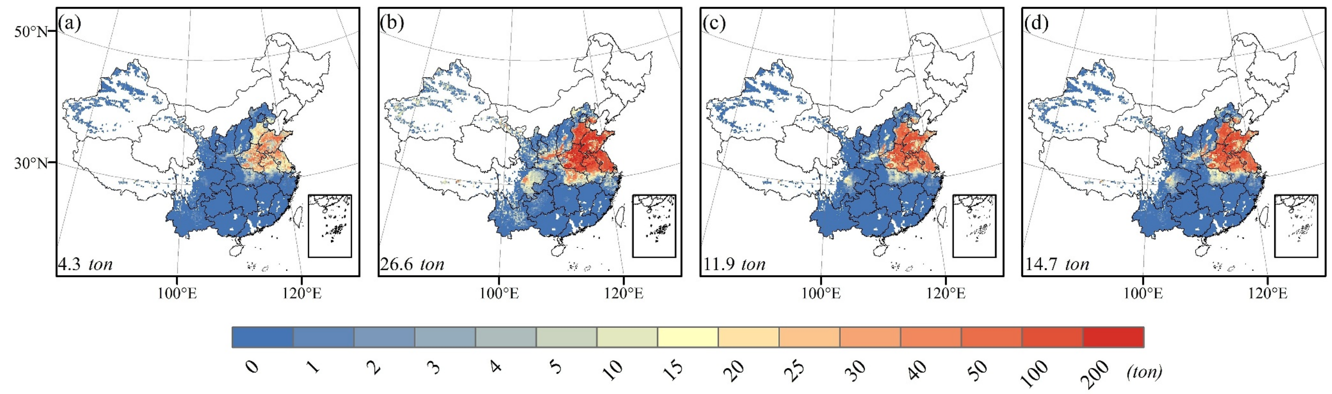

Figure 2. Spatial distribution of crop production loss (CPL) of winter wheat due to ozone damage averaged over 2013–2018 during the growing season. (a) M7-related CPL, (b) AOT40-related CPL, (c) SUM06-related CPL, (d) W126-related CPL. The number in the bottom of each panel represents the national mean CPL, and the unit is ton.

CPLs over other provinces. AOT40-related winter wheat production loss presents the largest value with the national mean of 26.6 ton, followed by SUM06-related and W126-related losses (11.9 and 14.7 ton). The M7-related CPL shows the lowest value (4.3 ton), about 0.2 times smaller than AOT40-related loss. These results further emphasize the large uncertainty of O_3-induced CPL by applying different dose-response relationships.

Provincial CPLs of winter wheat averaged over 2013–2018 derived from O_3 concentration-based metrics of M7, AOT40, SUM06, and W126 are presented in Figure 3. Severe agricultural losses are mainly located in Henan, Shandong, Hebei, Jiangsu, and Anhui provinces, as the areas cultivating huge amounts of winter wheat (Figure S4 in Supporting Information S1) and exposing to high concentrations of O_3 (Figure S3 in Supporting Information S1). The mean CPLs of winter wheat calculated by the four metrics for Henan, Shandong, Hebei, Jiangsu and Anhui provinces are 0.6–5.1, 0.7–4.3, 0.2–2.3, 0.3–2.3, and 0.3–2.0 Mt, respectively. The uncertainty of the diagnosed CPLs by these metrics in a province (e.g., Henan province) can be as high as 8.4 times, which will lead to significant biases when analyzing the impact of O_3 pollution on food security by using only one metric. Therefore, in order to reduce the potential bias, the ensemble mean based on M7-related, AOT40-related,

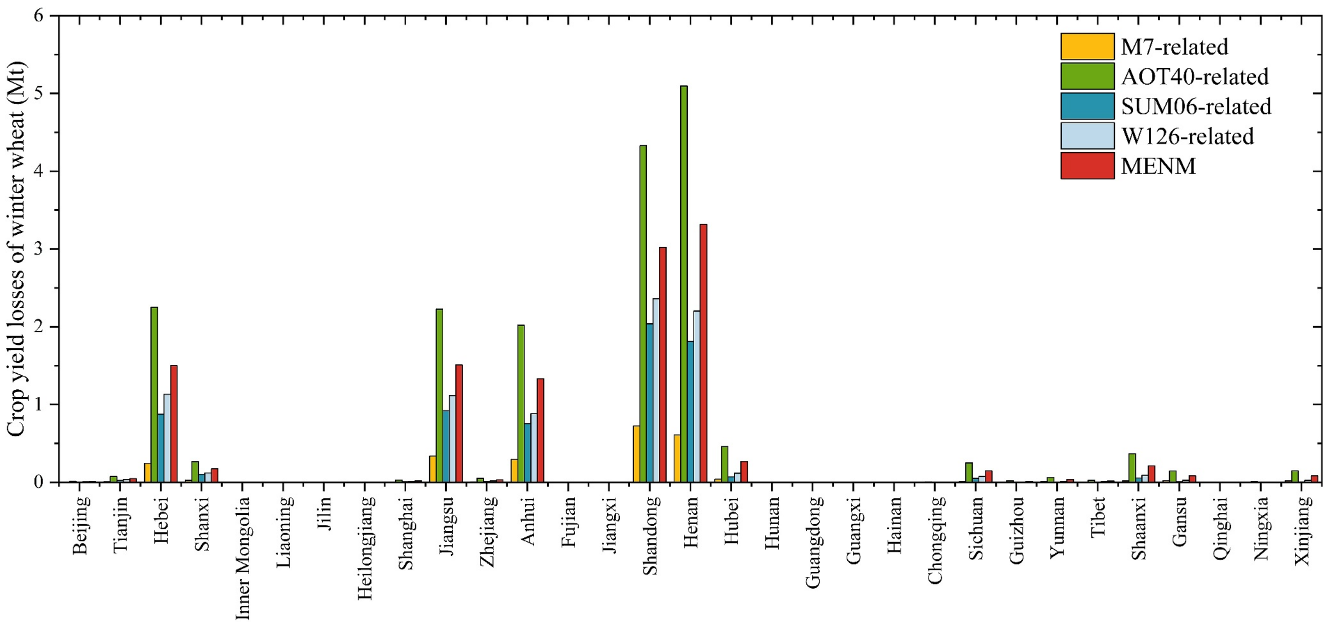

Figure 3. Crop production loss (CPL) for winter wheat based on each O_3 concentration-based metric and their ensemble mean in Chinese provinces averaged over 2013–2018 during the growing season. The yellow bars represent M7-related CPL. The green bars represent AOT40-related CPL. The blue bars represent SUM06-related yield loss. The light blue bars represent W126-related CPL. The red bars represent the ensemble mean. The unit of CPL is Mt.

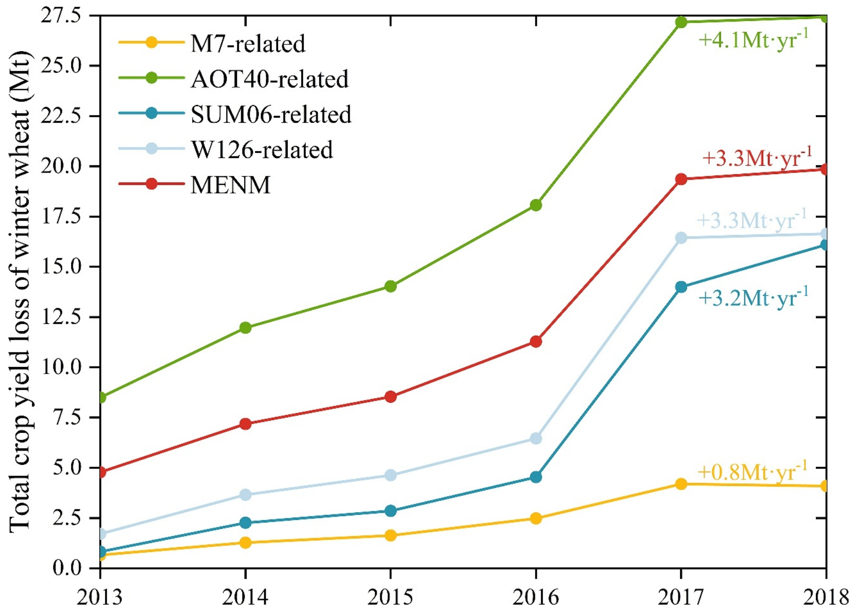

Figure 4. Annual variations of total crop production loss (CPL) of winter wheat based on each O_3 concentration-based metric and their ensemble mean in China during the growing season from 2013 to 2018. The yellow dotted line represents M7-related CPL. The green dotted line represents AOT40-related CPL. The blue dotted line represents SUM06-related CPL. The light blue dotted line represents W126-related CPL. The red dotted line represents MENM. The 6-year trends calculated under each condition are presented in values with the corresponding colors.

SUM06-related, and W126-related CPL are calculated, and the multi-metric ensemble mean (MENM) related CPL can reflect the more general result (Murphy, 1988; Zhu, 2005), with the values of 3.3, 3.0, 1.5, 1.5, and 1.3 Mt for Henan, Shandong, Hebei, Jiangsu and Anhui provinces, respectively.

Figure 4 shows the yearly variations of M7-related, AOT40-related, SUM06-related, and W126-related national CPLs for winter wheat from 2013 to 2018. Due to the increased wheat planting (the trend of winter wheat production during 2013–2018 is +1.5 Mt yr^{-1}) and the worsened O_3 pollution (the trend of O_3 concentration during the growing season during 2013–2018 is +3.4 $\mu g \cdot m^{-3} \cdot yr^{-1}$), the impact of O_3 damage on crop yield has been becoming more and more serious, and the 6-year trends of CPL derived from M7, AOT40, SUM06, and W126 are +0.8, +4.1, +3.2, and +3.3 Mt yr^{-1}, respectively. According to the value of MENM, the annual CPLs of winter wheat from 2013 to 2018 are 4.8, 7.2, 8.5, 11.2, 19.4, and 19.9 Mt, with the trend of +3.3 Mt yr^{-1}.

To quantify the contributions of O_3 concentration variation alone and crop production variation alone to CPL, two sensitive experiments are designed (Figure S5 in Supporting Information S1). From Figure S5 in Supporting Information S1, we can conclude that the increased O_3 concentration dominates the worsened CPL, with the contribution of 93.2% (89.6%) to the 6-year mean (trend) of CPL, which indicates that the serious O_3 pollution does have threatened the food security in China, and stricter control measures to mitigate O_3 pollution are urgently needed.

3.2. Future Damaging Effects of Ozone on Winter Wheat Production

Agricultural growing regions exposed to higher O_3 concentrations in the future during crop-growing seasons will lead to more reductions in crop yields. We further analyze the variations in annual mean O_3 concentrations during 2019–2099 relative to 2018 from CMIP6 simulations to represent O_3 damage under different SSP scenarios (in the section of future damage effects, the O_3 concentrations in 2018 are also obtained from CMIP6 as those during 2019–2099.). From Figure S6 in Supporting Information S1, we can find that future O_3 concentrations will continue to decrease in SSP1-2.6 with the trend of −0.3% yr^{-1}, which can help to ensure the safety of agricultural products. While the O_3 concentrations in SSP3-7.0 present a continuing upward trend with the value of +0.1% yr^{-1} through 2019–2099. Higher O_3 concentrations in the future will exacerbate the negative effects of O_3 on agricultural production.

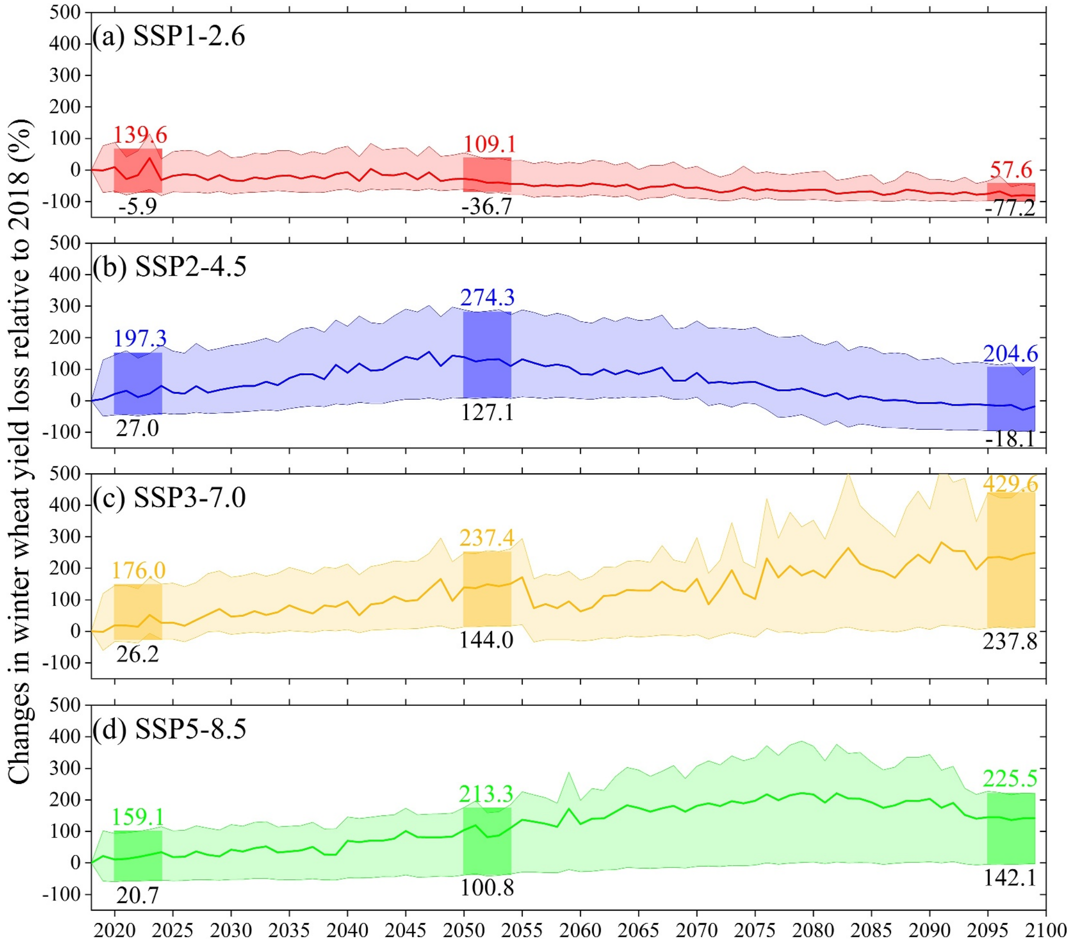

Figure 5. Future variations in crop production loss (CPL) of winter wheat during 2019–2099 relative to 2018 under different scenarios of (a) SSP1-2.6, (b) SSP2-4.5, (c) SSP3-7.0, and (d) SSP5-8.5 averaged over China based on CMIP6 simulations. The colored lines indicate the ensemble mean yield losses based on multi-O_3-related metrics, and the shades show the variation range among the four metrics (i.e., M7, AOT40, SUM06, and W126). The three bars in each panel show the 5-year mean values averaged over the early-century (2020–2024), the mid-century (2050–2054), and the late-century (2095–2099). The colored number on the top of each bar represents the uncertainty of range derived from the multi dose-response relationships, and the number in black on the bottom of each bar is the mean value.

Figure 5 shows the changes in future winter wheat yield loss associated with O_3 damage during 2019–2099 relative to 2018 from CMIP6 models. The deteriorating yield losses under high emission scenarios (SSP3-7.0 and SSP5-8.5) is worse than that under low emission scenarios (SSP1-2.6 and SSP2-4.5). According to the MENM-related winter wheat production loss, we can quantify that the changes in CPL will be reduced from −36.7% (127.1%) during the mid-century to −77.2% (−18.1%) during the late-century relative to 2018 under SSP1-2.6 (SSP2-4.5) due to the improved O_3 air quality (Figure S6 in Supporting Information S1), while the changed crop losses in SSP3-7.0 (SSP5-8.5) will be increased from +26.2% (+20.7%) during the early-century to +237.8% (+142.1%) during the late-century relative to 2018. For the range of uncertainty (i.e., the shades in Figure 5), the potential biases in changed losses of winter wheat by using different dose-response relationships will be enhanced (reduced) over time under SSP3-7.0 and SSP5-8.5 scenarios (SSP1-2.6 and SSP2-4.5 scenarios). Take SSP3-7.0 (SSP1-2.6) as an example, the uncertainty will be increased (decreased) from 176.0% (139.6%) during the early-century to 237.4% (109.1%) during the mid-century and 429.6% (57.6%) during the late-century. The severe CPL caused by O_3 in the future poses urgent demands on climate policies and agricultural protection technologies to ensure food security.

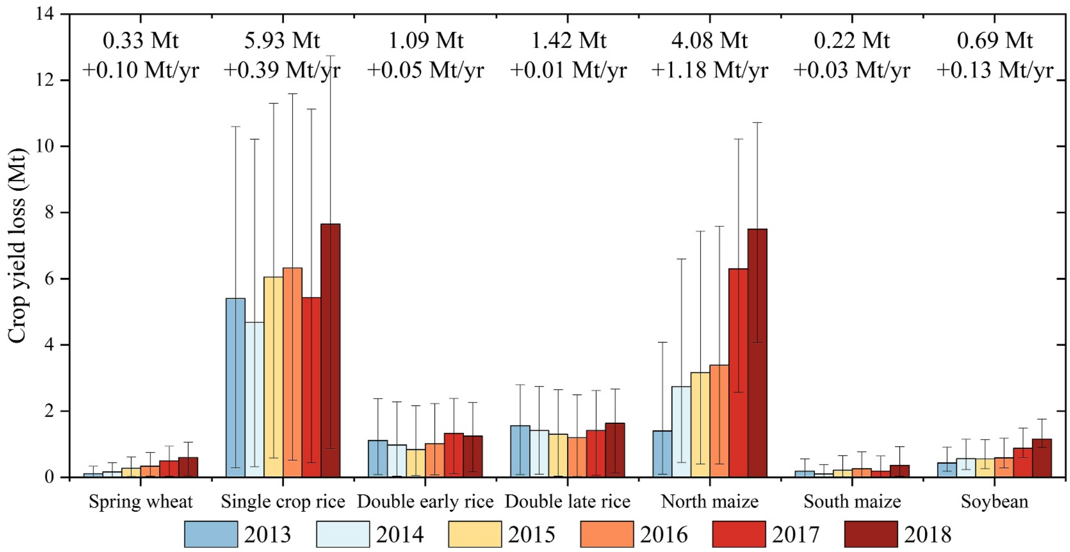

Figure 6. Annual crop production losses (CPLs) for spring wheat, single crop rice, double early rice, double late rice, north maize, south maize, and soybean based on multi-metric ensemble mean during their growing seasons from 2013 to 2018 in China. The error bar means the variation range derived from the four metrics (M7/M12, AOT40, SUM06, and W126). The number listed in the top represents the 6-year mean (trend) value for each crop.

3.3. Impacts of Ozone Pollution on Agriculture Productions of Other Crops

Figure 6 supplementally presents the yield losses of the other crops (spring wheat, single crop rice, double early rice, double late rice, north maize, south maize, and soybean) due to O_3 stress during their growing seasons from 2013 to 2018. The 6-year means (trends) of CPL based on multi-metric ensemble mean for these crops are 0.33 Mt (+0.10 Mt yr^{-1}), 5.93 Mt (+0.39 Mt yr^{-1}), 1.09 Mt (+0.05 Mt yr^{-1}), 1.42 Mt (+0.01 Mt yr^{-1}), 4.08 Mt (+1.18 Mt yr^{-1}), 0.22 Mt (+0.03 Mt yr^{-1}), and 0.69 Mt (+0.13 Mt yr^{-1}), respectively. In general, we can finally quantify that 8.5% (12.2 Mt) of wheat yields, 3.8% (8.4 Mt) of rice yields, 1.6% (4.3 Mt) of maize yields, and 4.8% (0.7 Mt) of soybean yields are lost due to O_3 pollution during 2013–2018 in China.

Future variations in yield losses of spring wheat, single crop rice, double early rice, double late rice, north maize, south maize, and soybean associated with O_3 damage under different SSP scenarios are added in Figure 7. Relative to 2018, future production losses of all the analyzed crops will be decreased during the early-, mid-, and the late-century under the clean scenarios (SSP1-2.6 and SSP2-4.5), while all their CPLs will be continuously enhanced under SSP3-7.0 scenario. In general, it can be predicted that the worsened O_3 pollution under SSP3-7.0 scenario will cause 283.6% (170.3%, 479.4%, 168.0%) increase in wheat (rice, maize, soybean) production losses during the late-century relative to 2018 in China, while the improved O_3 air quality under SSP1-2.6 scenario will decrease 73.8% (69.3%, 80.8%, 75.5%) wheat (rice, maize, soybean) production losses during the late-century relative to 2018 in China.

4. Conclusions and Discussions

China is experiencing severe ozone (O_3) pollution, and the high concentration of O_3 can damage plant leaves to lead to reductions in crop yields, which will pose a non-negligible threat to national food security. In order to explore the impacts of O_3 exposure on agricultural crops, observed O_3 from China National Environmental Monitoring Centre (CNEMC) during 2013–2018 and predicted O_3 under different Shared Socioeconomic Pathways (SSPs) scenarios from Coupled Model Intercomparison Project Phase 6 (CMIP6) during 2019–2099 are selected to construct concentration-based metrics (i.e., M7/M12, AOT40, SUM06, and W126) with the aim to quantify O_3-induced production losses in the four main types of human's foodstuffs (i.e., wheat, rice, maize, and soybean).

Concentration-based metrics are used to qualitatively describe the damaging effect of O_3 on crop yields, and a good consistency in the distribution of O_3 stress are found among these metrics, with high values over eastern

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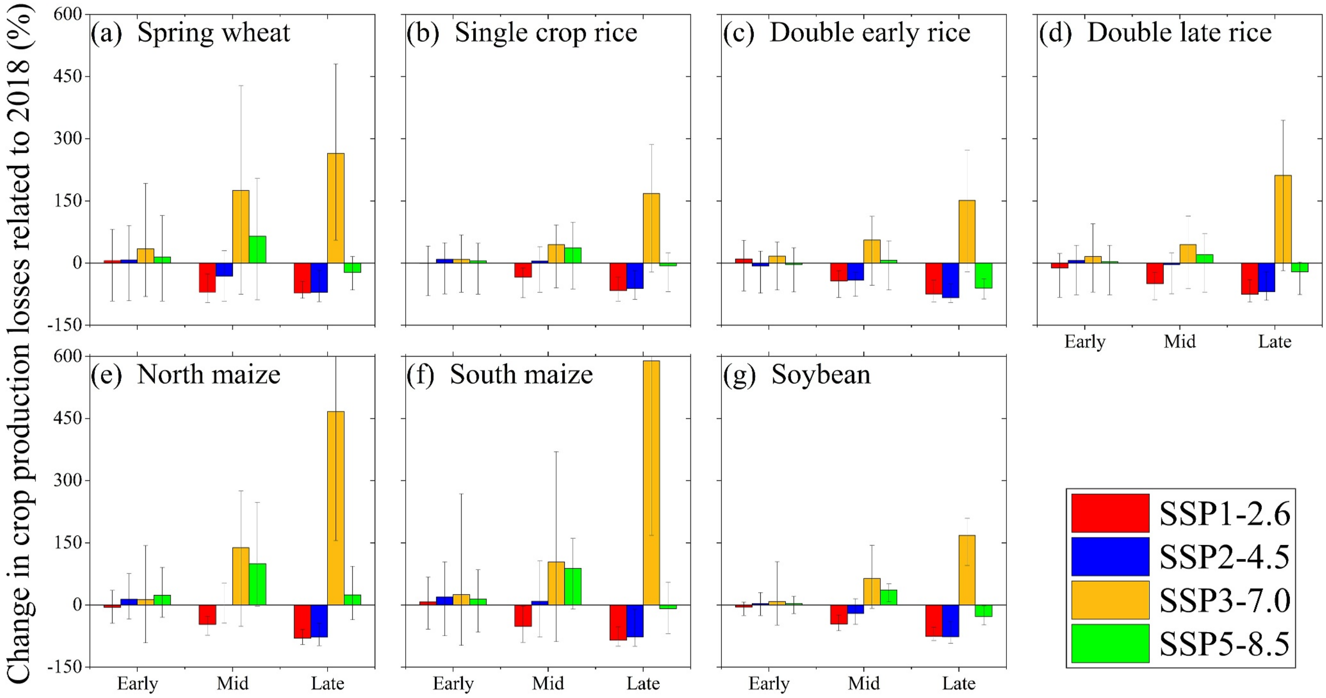

Figure 7. Future variations in crop production loss (CPL) of (a) spring wheat, (b) single crop rice, (c) double early rice, (d) double late rice, (e) north maize, (f) south maize, and (g) soybean based on multi-metric ensemble mean during the early-century (2020–2024, denoted as Early in X coordinate), mid-century (2050–2054, denoted as Mid in X coordinate) and late-century (2095–2099, denoted as Late in X coordinate) relative to 2018 under SSP1-2.6 (red bar), SSP2-4.5 (blue bar), SSP3-7.0 (yellow bar) and SSP5-8.5 (green bar). The error bar represents the variation range derived from the four metrics (M7/M12, AOT40, SUM06, and W126).

China and low values over southern China. However, different metrics present large biases in evaluated crop production loss (CPL), for example, national averaged AOT40-related winter wheat loss (26.6 ton) is 6.2 times higher than M7-related loss (4.3 ton) during 2013–2018, which implies that significant uncertainty will be concluded when analyzing the impact of O_3 pollution on food security by using only one metric.

In order to reduce the potential bias, multi-metric ensemble mean (MENM) related CPL is finally calculated. According to the CPL derived from MENM, the impact of O_3 damage on crop yield (e.g., winter wheat) has been becoming more serious in China, with the trend of +3.3 Mt yr^{-1} during 2013–2018, and the worsened O_3 pollution is the dominant factor compared to enhanced crop yields for the increased CPL, with the contribution of 89.6% to the 6-year trend. Future higher O_3 concentrations during crop growing seasons under the scenario of SSP3-7.0 (SSP5-8.5) will make China face a more serious food crisis with the changed CPL (e.g., winter wheat yield loss) increased from +26.2% (+20.7%) during the early-century to +237.8% (+142.1%) during the late-century relative to 2018. While, the low emission scenario of SSP1-2.6 (SSP2-4.5) can improve O_3 air quality, and the changes in winter wheat production losses will be reduced from −36.7% (127.1%) during the mid-century to −77.2% (−18.1%) during the late-century relative to 2018.

In general, 8.5% (12.2 Mt) of wheat yields, 3.8% (8.4 Mt) of rice yields, 1.6% (4.3 Mt) of maize yields, and 4.8% (0.7 Mt) of soybean yields are lost due to O_3 pollution during 2013–2018 in China. The worsened O_3 pollution under SSP3-7.0 scenario will cause 283.6% (170.3%, 479.4%, 168.0%) increase in wheat (rice, maize, soybean) production losses during the late-century relative to 2018, while the improved O_3 air quality under SSP1-2.6 scenario will decrease 73.8% (69.3%, 80.8%, 75.5%) wheat (rice, maize, soybean) production losses during the late-century relative to 2018. All these results clearly indicate that the serious O_3 pollution does have damaged the crop yields in China, and stricter control measures are urgently needed to improve O_3 air quality for ensuring food security in future.

There are also some limitations that should be further discussed in our on-going studies:

1. The historical O_3 concentrations during 2013–2018 collected from CNEMC are mainly observed over urban areas, which may cause biases in studying the impact of O_3 damage on crop yields over farmland.

2. The evaluation of historical CPL relies on accurate production data. The gridded crop production data comes from the fusion of GAEZ (Global Agro Ecological Zones) and CSY (China Statistics Yearbook), and the annual provincial yield data from CSY can only be available until 2018. Therefore, the accurate assessment of O_3-driven crop production losses in China after 2018 has not been quantified.
3. It is essential to acknowledge that crop ecology is an open ecosystem interacted by climate-plant physiology-environment, which means that crop yield can be modulated not by air pollutants but also by meteorological variables (Hoogenboom, 2000; Lecerf et al., 2019; Rauff & Bello, 2015). Therefore, a simple multivariate analysis, following the method used in Fishman et al. (2010), has been performed to quantitatively compare the relative contribution of meteorological factors (primarily temperature and humidity) and ozone pollutant on yields of winter wheat during 2013–2018 over the typical large crop province of Hebei. As Figure S7 in Supporting Information S1 shows, the regression result produces a negative contribution of 7.2% for worsened O_3, while significant positive contribution of 41.9% is calculated for changed temperature and humidity, which means that meteorological factors have a greater impact on crop yield, although worsened ozone pollution exacerbates the loss of agricultural production. Therefore, multi-factors including meteorological variables and air pollutants should be considered in future study to detailedly quantify the evolution characteristic of crop production losses.
4. Under global warming, the increased frequency of extreme weather events such as droughts and heat waves have a profound implication for crop production (Beillouin et al., 2020; Brás et al., 2021; Lesk et al., 2016; Lobell & Burke, 2008; Schmitt et al., 2022). This underscores the necessity of incorporating extreme weather effects into future crop yields assessments, and CMIP6 can provide robust predictions for extreme weather highlighting its potential in assessing future food security (Cook et al., 2020; Ukkola et al., 2020).
5. Furthermore, the definition of the growing season is a crucial variable in calculating CPL (Y. Wang et al., 2022) due to the high sensitivity of vegetation phenology to climate (Jiao et al., 2022; Parmesan & Yohe, 2003; Walther et al., 2002). The increasing frequency of extreme weather events further introduces substantial uncertainty regarding crop survival during the growing season. Consequently, the decrease of potential climate-benefiting gross primary productivity (GPP) attributed to dynamic O_3 damage in the context of climate warming is an issue that needs further discussion.

Data Availability Statement

All data used in this paper are publicly available. The observed hourly O_3 concentrations during the period of 2013–2018 were obtained from China National Environmental Monitoring Centre (CNEMC, http://www.cnemc.cn/). Hourly O_3 concentrations during 2018–2099 are obtained from future projection of Scenario Model Intercomparison Project (ScenarioMIP) in CMIP6 (https://esgf.nci.org.au/projects/cmip6-nci/). The gridded crop production data can be obtained from Global Agro Ecological Zones (GAEZ, https://gaez.fao.org/). The annual provincial yield data is from China Statistics Yearbook (CSY, https://data.stats.gov.cn). Chinese administrative divisions are archived at https://github.com/NUISTqqw/Data4Sci/. Topography data from the STRM data set are available at https://www.earthdata.nasa.gov/sensors/srtm. The data analysis are performed using Python 3.8 (https://www.python.org/). Visualization are achieved using Origin 2021 (https://www.originlab.com/) and ArcMap 10.8 (https://desktop.arcgis.com).

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