Surface ozone impacts on major crop production in China from 2010 to 2017

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Abstract. Exposure to elevated surface ozone is damaging to crops. In this study, we performed an analysis of temporal and spatial distributions of relative yield losses (RYLs) attributable to surface ozone for major crops in China from 2010 to 2017,

15 by applying the AOT40 metrics (hourly ozone concentration over a threshold of 40 ppbv during the growing season) simulated by chemical transport model. The major crops in China include wheat, rice (including double early & late rice, and single rice), maize (including north and south maize) and soybean. The aggregated production and associated economic losses in China and major provinces were evaluated by combing annual crop production yields with crop purchase prices. We estimated that, from our model simulations, the national annual average AOT40 in China increased from 21.98 ppm h in 2010 to 23.85 ppm

20 h 2017, with a peak value of 35.69 ppm h in 2014. There exists significant spatial heterogeneity for the AOT40 and RYLs across the four crops due to the different growing seasons for each crop. We estimated that national mean RYLs were 11.45%-19.74% for wheat, 7.59%-9.29% for rice, 0.07%-3.35% for maize, and 0.87%-2.74% for soybean during 2010 to 2017. The associated ozone-induced annual average crop yield losses were estimated 13.81–36.51 million metric tons (Mt) for wheat, 16.89–20.03 million Mt for rice, 4.59–8.17 million Mt for maize, and 0.27–0.34 million Mt for soybean, which accounted for

25 annual average economic loss of $9.55 billion, $8.53 billion, $2.23 billion, and $0.22 billion individually over the 8 years. Our results provide first, long-term quantitative estimation of crops yield losses and their economic cost from surface ozone exposure in China before and after the China Clean Air Act, and improve the understanding of the spatial sensitivity of Chinese crops to ozone impacts.

1 Introduction

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Tropospheric ozone, as a secondary air pollutant, is harmful to both human and vegetation health (Booker et al., 2009; Van Dingenen et al., 2009; Brauer et al., 2013). Since the 19th century, rapid industrialization and urbanization have significantly elevated the background ozone concentration in the Northern Hemisphere (The Royal Society, 2008). As a greenhouse gas that is not directly emitted by human activities, tropospheric ozone is mainly generated from sunlight driven photochemical

35 oxidation of volatile organic compounds (VOC), carbon monoxide or methane in the presence of NO_X (Atkinson, 2000). In the past few decades, the strong linkage between fossil fuel usage and economic growth boosted emissions of ozone precursors in China. Since 2012, due to the severe fine particulate matter ($PM_{2.5}$) pollution in China, the Chinese government has adopted a stringent emission and pollution monitoring and control policy (the so-called Air Pollution Prevention and Control Action Plan (APPCAP), Zhang et al., 2016). The APPCAP has led to a significant decline of air pollutants emissions, including 17%

40 decreases of anthropogenic emission of NO_x, 27% of CO, and 62% of SO_2 from 2010 to 2017 (Zheng et al., 2018). These significant emissions reductions have led to -33% decline of annual $PM_{2.5}$ in China from 2013 to 2017, and avoided 0.41 million premature deaths (Zhang et al., 2019). At the same time, however, anthropogenic emission of VOC increased by 11% due to the lack of effective emission controls (Zheng et al., 2018) and surface observations show that the ozone concentration in China still reveals a tendency of increasing (Wang et al., 2019; Li et al., 2018 & 2019; Lu et al., 2018, 2020).

45 The growth of ozone concentrations in China has led to emerging concerns (Lu et al., 2018, 2020). As indicated in many biological and ecological studies, high ozone concentration can seriously damage vegetation and substantially impair crop yield, which leads to economic costs and threatens food security (Krupa et al., 1998; Mills et al., 2007; Van Dingenen et al., 2009, 2018; Avnery et al., 2011a, b). Based on different field-based concertation-response studies, for the year 2000 surface ozone exposure induced crop yield reductions of 3.9%-15% for wheat, 2.2% -5.5% for maize, and 8.5%-14.0% for soybeans,

50 with global crop production loss of 79-121 million Mt (Avnery et al., 2011a; Tang et al., 2013). For Eastern Asia, the ozone-induced maize reduction loss is around 3.8%, 17% for wheat, and as high as 21% for soybean in 2000 (Avnery et al., 2011a; Tang et al., 2013). Throughout China specifically, by 2020 exposure to surface ozone was projected to decrease maize production by 7.2%, wheat (including both winter and spring wheat) by 13.4%- 29.3%, and soybean by 18%-21% (Aunan et al., 2000; Tang et at., 2013; Feng et al., 2015). A recent study by Lin et al. (2018) estimated that exposure to surface ozone in

55 2014 could cause 78.4 million metric tons (Mt) of production losses from all crops, including winter wheat, rice and maize. By using observational data, the exposure to surface ozone in the North China Plain (NCP) was estimated to cause annual average of 2.3 billion USD loss for maize and 9.3 billion USD for wheat from 2014 to 2017 (Feng et al., 2020; Hu et al., 2020). To date, very few studies have investigated the long-term trends and spatial patterns of ozone impacts on crop production in China. Previous studies mainly focused on the crop production loss from ozone at the global scale, or on short time periods

60 and/or regional spatial coverage (Rosenzweig et al. 2014; Zhao et al. 2017; Lin et al., 2018; Hu et al., 2020; Feng et al., 2019, 2020; Zhao et al., 2020). In this study, we focus on the long-term ozone-exposure impact analysis from 2010 to 2017 in China to assess the yield losses of four major crops (wheat, maize, rice, and soybean) and evaluate their associated economic losses.

The study aims to present a comprehensive analysis of ozone-induce crop yield losses and economic impacts in the agriculture sector before and after the China APPCAP. Such an analysis is expected to provide scientific support to policymakers for their decision making.

2 Methodology

2.1 Model simulated hourly ozone and surface observation in China

Hourly ozone concentration over China from 2010 to 2017 were simulated by using a state-of-the-art global chemistry model (CAM_Chem, Lamarque et al., 2012). The original model was run at a horizontal resolution of 1.9° ×2.5° (Zhang et al, 2016; 2020), and then regridded to 1°×1° to match the crop production data (see section 2.2). The anthropogenic emissions in China from 2010 to 2017 are from the Multi-resolution Emission Inventory (MEIC) developed by Tsinghua University (http://meicmodel.org/, last access July 15, 2020). Emissions outside China are from the Community Emissions Data System (CEDS) which were prepared for the Coupled Model Intercomparison Project Phase 6 (CMIP6) experiments (Hoesly et al., 2018). Hourly surface ozone was saved from 2010 to 2017 from the model simulation. We then adjusted the model simulated surface ozone from its higher altitude (usually above 30 meters) to a lower altitude (usually 3-5 meters at the ambient observation sites), following previous methods (Van Dingenen et al., 2009; Zhang et al., 2012).

We first evaluated the model's performance by comparing the model simulated AOT40 with the surface observation during the growth season (April to September) from 2013 to 2017, which were downloaded from National Environmental Monitoring Center (CNEMC) Network (http://106.37.208.233:20035/). It collects at least 100 million environmental monitoring data from 1497 established air quality monitoring stations annually for national environmental quality assessment. The ozone observation data before 2013 were not available (Lu et al., 2018, 2020). In general, the model simulated AOT40 values were lower than the observation data, with normalized mean bias ranging from -5% in 2015 to -28% in 2017 (Table S1). This indicates that our estimation on crop production loss and associated economic loss are conservative estimations.

2.2 Ozone crop metrics

In order to assess the crop yield loss from exposure to surface ozone, many different crop-ozone matrixes are developed to measure the chronic ozone exposure risk of vegetation (e.g., Wang and Mauzerall, 2004; Van Dingenen et al., 2009; Avnery et al., 2011a, b;). In this study, we adopted the ozone metric of AOT40 which is among the commonly used metrics in crop yield assessment. AOT40 is calculated by summing up hourly ozone exposure concentration over the threshold of 40 ppbv during the 12 h (08:00—19:59 China Standard Time) (equation 1). By counting concentration over 40ppbv, AOT40 is able to sensitively capture the influence of extremely high ozone concentration (Van Dingenen et al., 2009; Hollaway et al., 2012). In a synthesis study by Mills et al. (2007), the AOT40 showed a statistically significant relationship with many crops.

$$AOT40 = \sum_{i=1}^{n}([O_3]_i - 0.04), for\ [O_3]_i \geq 0.04\ ppm \tag{1}$$

In the equation (1), $[O_3]_i$ denotes the hourly ozone concentration level during daylight hours (8:00am – 7:59pm, GMT+8) at each grid cell (*i*), *n* is the total hours of growing season which was counted as the 3-month harvest season based on the crop calendar (Lin et al., 2018), or 75 days composed by 44 days and 31 days before and after the anthesis dates (Feng et al., 2019, 2020). Growing seasons for wheat, rice, maize and soybeans were acquired from Major World Crop Areas and Climate Profiles (MWCACP), and the Food and Agriculture Organization of the United Nation (FAO) (Lin et al., 2018; Zhao et al., 2020). In this study, we focused on four major crops—wheat, rice (including double early rice and late rice, and single rice), maize (including north maize and south maize), and soybean.

2.3 Crop relative yields and economic losses

In our study, relative yield (RY) was calculated based on the exposure-response function (ERF) provided by Mills et al. (2007), where RY is in % and AOT 40 is in ppm h (Table 1). The ERF for north maize and south maize is the same with different growing seasons and growing areas (Table 1; NBSC, 2018; Zhou et al., 2019; Zhao et al., 2020). The same ERF applies to all the rice, with differences in growing season and provinces as well (Table 1).

The relative yield loss (RYL_i) in each grid cell was then calculated in equation (2).

$$RYL_i = 1 - RY_i \tag{2}$$

The crop production loss (CPL_i) was then calculated using equation 3 (Wang and Mauzerall, 2004; Dingenen et al., 2009; Avnery et al., 2011a,b):

$$CPL_i = CP_i \times \frac{RYL_i}{1 - RYL_i} \tag{3}$$

where CP_i is the annual crop production with unit of 1000 Mt per year. Grid cell annual crop production data for major crops was originally developed by Van Dingenen et al. (2009) from USDA national and regional production numbers and Agro-Ecological Zones suitability index. It contains global crop production data in 2000 with horizontal resolution of 1°×1°. We then scaled the annual national total crop yields in China to match the yearly data from the Statistical Yearbook of China from 2010 to 2017 (http://www.stats.gov.cn/tjsj/ndsj/2019/indexeh.htm, last accessed 26th, March, 2020). For provinces growing both double and single Rice (such as Zhejiang and Jiangxi, see the highlighted bold notes in Table 1), the fractions for double and single rice production were scaled based on the production data from the National Bureau of Statistics (http://data.stats.gov.cn, last accessed 26th, March, 2020). For provinces growing double early/late rice only, the rice productions were assumed to be equal for each rice.

National average relative yields loss (*ARYL*, unit of %), is then calculated based on CPL_i and CP_i to identify the fractions of production loss in total crop production (Equation 4):

$$ARYL_i = \frac{CPL_i}{CP_i + CPL_i} \times 100\% \tag{4}$$

National economics costs for each crops (EC_p) were then quantified by multiplying the purchase price in each year using equation 5:

$$EC_p = CPL_p \times Crop\ Price_p \tag{5}$$

125 where $Crop\ Price_p$ stands for the purchase price for each crop in every year with unit of $/Mt. Crops purchase prices were acquired from the FAOSTAT (http://www.fao.org/faostat/, last accessed 26th, March, 2020). The purchase price from the FAOSTAT is not available for the major crops in 2017 except for maize, so we used the 3-year average from 2014 to 2016 to calculate economic losses in 2017 for wheat, rice, and soybean. From 2010 to 2017, soybean has the highest crop purchase price, ranging from 677.9 $/ton to 869.7 $/ton, followed by rice (296.6 $/ton to 559.9 $/ton), wheat (279.5 $/ton - 391.4 $/ton)

130 and maize (252.2 $/ton – 489.1 $/ton). For soybean, wheat and maize, the purchase price usually peaks in 2014 or 2015, which contributed to the peak economics loss in these years (see section 3.3).

3 Results

3.1 Temporal and spatial distribution of ozone concentration change

Since the four crops have distinct growing seasons (Table 1), thus different accumulated AOT40 values, here we present the

135 annual accumulated AOT40 in China from 2010 to 2017. From Fig. 1 we see that the 8-yr average annual accumulated AOT40 values are usually larger than 16 ppm h, with hotspots identified in western China (40-56 ppm h), Beijing-Tianjin-Hebei (a.k.a. JJJ, 32-40 ppm h), northeastern China (24-32 ppm h) as well as Yangtze Delta Region (YRD, Fig. S1). At provinces level, Xizang (41.47 ppm h for 8-year average), Tianjin (34.79 ppm h) and Qinghai (34.51 ppm h) are the top three provinces with the highest annual accumulated AOT40 (Table S2). For the temporal changes, we conclude that the national annual

140 accumulated AOT40 has been increasing from 21.98 ppm h in 2010 to 23.85 ppm h in 2017, with peak of 35.69 ppm h in 2014 (Fig. 2). The increases trend of ozone in China even though the precursors were decreasing after 2010 (Li et al., 2017; Zheng et al., 2018), were also reported in previous studies utilizing both surface observations and modelling data (Lu et al., 2018, 2020; Li et al., 2020; Liu and Wang, 2020a), and were caused by a combination of unfavourable meteorological conditions, the unmitigated missions of volatile organic compounds and the decrease of PM$_{2.5}$ (Li et al., 2018, 2019, 2020; Liu and Wang,

145 2020b). The peak value of the annual accumulated AOT40 in 2014 as well adjacent years were mainly caused by the high ozone values in the western China (Fig. S1), mainly dominated by the transboundary transport from foreign sources driven by strong westerly winds and stratosphere-troposphere exchange (Zhang et al., 2008; Wang et al., 2011; Ni et al., 2018; Lu et al., 2019).

3.2 Growing-season ozone concentration and relative yield loss (RYL)

150 During the growing season for the wheat (March, April and May), the accumulated AOT40 concentration revealed to be higher in the Tibet Plateau and YRD, and lower in the south China, such as Hainan, Guangdong and Guangxi (Fig. 3a; Table S3). At

province level (Table S3), the highest AOT40 is in Xizang (14.99 ppm h), following by Yunan (12.60 ppm h) and Qinghai (11.77 ppm h), with the lowest values in Hainan (4.43 ppm h). We also notice that the AOT40 values for wheat were decreasing in the western China, but increasing in the middle and eastern China from 2010 to 2017 (Fig. S2), which were caused by a

155   combination of unfavourable meteorological conditions and decreased anthropogenic emissions (Liu and Wang, 2020a). The RYL for wheat have the similar spatial patterns as AOT40, with highest of 25.14% in Xizang for the 8-yr average, and lowest of 8.13% in Hainan (Table S3).

The AOT40 values for double early rice (May, June, July) are lower than those for wheat (Fig. 3b), with highest province in Anhui (12.09 ppm h), and lowest in Hainan (1.84 ppm h; Table S4). The AOT40 values for double late rice are much lower

160   than the early rice (Fig.3c), with highest in Fujian (6.47 ppm h), and lowest in Yunan (2.86 ppm h; Table S4). The spatial distribution of AOT40 for the early and late rice varies as well, with the hotspots in eastern China for early rice and southern China for late rice (Figs. S3-S4). The RYLs ranges from 10.71% in Anhui to 7.11% in Yunan for the 8-yr average (Table S4). For the single rice, the NCP experiences high ozone exposure during the growing season (AUG, SEP, OCT), and lower in southern China (Fig. 3d). AOT40 level ranges from 1.0 ppm h (Yunnan in 2017) to 14.1 ppm h (Tianjin in 2015). Highest

165   RYLs for the single rice are identified in the North China Plain including Tianjin (8-year average RYL of 10.22%), Shanxi (9.81 %), and Henan (9.67%; Table S5).

Hotspots for the AOT40 values for the north maize during growing season (JUNE, JULY, AUG) are identified in the NCP (Fig. 3e; Fig. S7), including Tianjin (20.24ppm h), Beijing (17.92 ppm h), and Hebei (17.80 ppm h). The provincial averaged RYLs range from 0.48% in Qinghai to 5.29% in Tianjin (Table S6). When looking at the AOT40 values for the south maize

170   (AUG, SEP, OCT), we found that they are much lower than the north maize, with the highest in Jiangsu (8.18 ppm h for 8-yr average) and lowest in Yunan (2.02 ppm h). For the spatial pattern, the AOT40 values are higher in the western China, but lower in the south China (Fig. 3d; Fig. S7). The 8-year averaged RYLs for each province is all below 1% (Table S6).

The growing seasons for soybean are the same as north maize, and thus they have the same hotpots as in NCP (Fig. 3e). For the 8-yr average, the highest AOT40 values is in Tianjin (20.2 ppm h with RYL of 11.48%), followed by Beijing (17.9 ppm h

175   with RYL of 8.79%), and Hebei (17.8 ppm h with RYL 8.65%) (Table S7).

3.3 Crop production loss (CPL)

From the Statistical Yearbook of China, the national wheat production increased from 115.19 million Mt in 2010 to 134.34 million Mt in 2017, which are mainly planted in the NCP. From equation 3, we estimated that on average, 26.42 million Mt of wheat will be lost in China due to surface ozone exposure, ranging from 13.81 million Mt in 2010 to 36.51 million Mt in 2015

180   (Fig. 4; Table S8). The annual national wheat CPLs in China are comparable to the total wheat production in France (29.5 to 42.8 million Mt from 2010 to 2017), which is the fifth largest wheat production in the world (http://www.fao.org/faostat/en/#data/QC, accessed November 30, 2020). Fig. 5 shows the CPL for each province in China from 2010 to 2017, with the top 5 provinces including Henan (5.23 million Mt for 8-yr average), Shandong (4.77), Hebei

(2.79), Jiangsu (2.66), and Anhui (2.58). We conclude that the wheat CPL due to ozone exposure were increasing from 2010
to 2017, with the peak year varying from province to province, but generally late than 2014 (Table S8). The hotspots for the
wheat product losses were in the NCP, inconsistent with the patterns of RYL (Fig. S2), which is not surprising since the regions
with high RYL, such as western China, usually have very limited wheat productions.

National double rice (including both early and late rice) production ranges from 77.94 million Mt to 80.70 million Mt from
2010 to 2017. We estimated that the national CPL for the early rice is between 3.51 million Mt and 3.92 million Mt in China
with 8-yr average of 3.60 million Mt (Fig. 3; Table S9). The CPL for the late rice is comparable with the early rice, ranging
from 3.21 to 3.93 with 8-yr average of 3.61 million Mt (Fig. 3; Table S10). The CPL for double early and late rice both peak
in 2014, but with different years for lowest values (Tables S9 and S10), highlighting the differences in the calculations of the
growing season (Table 1). In China, there are more provinces (27) growing single rice than the double rice. The CPLs for the
single rice are also higher than the double rice, ranging from 10.00 to 12.42 million Mt, with 8-yr average of 11.37 million Mt
(Fig. 3; Table S11). The leading provinces with the highest CPL for the single rice are Anhui (1.69—2.14 million Mt from
2010 to 2017), Jiangsu (1.55—1.91 million Mt), Hubei (1.13—1.52 million Mt), and Sichuan (1.13—1.52 million Mt), which
are all exceeding 1 million Mt for the 8-yr average (Fig. 5; Table S11). CPLs for most provinces were shown to peak in 2015
(Fig. 6). The annual CPLs for all the rice range from 16.89 million Mt in 2010 to 20.03 million Mt in 2014, with 8-yr average
of 18.58 million Mt, comparable to the annual rice productions in Philippines, which is the 8th largest rice produce in the world
(from 15.77 to 19.28 million Mt from 2010 to 2017, http://www.fao.org/faostat/en/#data/QC, accessed November 30, 2020).

Maize in China were mainly planted in NCP and northeastern China with north maize production dominates the total maize
production (82%). The annual maze production ranging from 177.54 million Mt in 2010 to 265.16 million Mt in 2015. We
estimated that 8-yr annual average CPL for maize were 6.12 million Mt, with the peak value of 8.17 million Mt in year 2015,
and lowest value of 4.59 million Mt in 2017 (Fig. 3), with largest contributions from Hebei (1.02—1.81 million Mt), Shandong
(0.81—1.31 million Mt), and Henan (0.53—0.85 million Mt) (Table S12; Fig. S9). The annual national maize CPLs in China
are comparable to the annual yields in Hungary, which ranks as 18th maize production in the world.

Soybean mainly grows in the NCP as well. The total soybean production in China decreased from 15.08 million Mt in 2010 to
11.79 million Mt 2015, and then increased slightly to 13.13 million Mt in 2017. Heilongjiang is the largest soybean producer
which contributes around 50% of the national soybean production (8-year average of 6.38 million Mt), followed by Anhui
(1.25 million Mt) and Henan (1.03 million Mt). We estimated that the ozone-induced CPL for soybean ranges from 74 thousand
Mt in 2017 to 338 thousands Mt in 2010, with 8-yr annual average of 263 thousands Mt (Fig. 4; Table S13). The lowest CPL
in 2017 was caused by the lower AOT40 values in the northeastern China (Figs. S1 and S8). Heilongjiang, Hebei, and Henan
are the three provinces with the highest CPL, with 77, 51, 41 thousand tons loss on average individually (Table S13).

3.4 National average relative yield loss (ARYL) and economic loss (EC)

215   From Fig. 7, we conclude that wheat has the largest national ARYL, ranging from 11% to 22% from 2010 to 2017, comparable with previous estimates: 14% in 2015 estimated by Lin et al. (2018) using regional model simulation, and 20.1-33.3% from 2015 to 2018 estimated by Zhao et al. (2020) using nationwide ozone monitoring data. National ARYLs for rice are around 8% - 9%, ranking in the second place among the four crops. Lowest ARYLs are observed for south maize (0-1%). It is noteworthy that, for most crops, the highest national ARYLs were observed in 2014 while the lowest values were observed in

220   2010 for wheat and 2017 for other three crops (Fig. 7).

When converted to EC, we estimated that 3.86 billion to 14.29 billion\$ would be lost nationally due to surface ozone exposure on wheat (Fig. 8a), with the top five provinces all above 1 billion \$, including Henan, Shandong, Hebei, Jiangsu and Anhui (Table S8). Our estimates are consistent with previous studies, which reported 10.3 billion and 10.7 billion \$ for wheat in 2015 and 2016 (Feng et al., 2019). National economic loss for double early and late rice increase consistently from 2.05 billion \$ to

225   3.87 billion \$ (Fig. 8a). The top three provinces with highest losses are Hunan, Jiangxi, and Guangzhou, with 8-yr average of 0.80 billion, 0.79 billion and 0.47 billion losses individually. For the single rice, national economic loss ranges from 2.96 billion to 6.49 billion \$ (Fig. 8a), with top provinces in Anhui (8-yr average 0.87 billion \$), Jiangsu (0.80 billion \$) and Hubei (0.63 billion \$). The ECs for the north maize ranges from 1.15 billion to 3.33 billion, much higher than the south maize (Fig. 8b). Soybean has the lowest economic losses compared with the other three crops, ranging from 55 million to 291 million \$

230   annually (Fig. 8b), with the major contribution from Heilongjiang province (51 – 83 million \$).

4 Discussions

Surface ozone emerged as an important environmental issue in China, and were shown increasing trend for the past few years using both modelling and observation data, though strict clean air regulations have been implemented in China after 2013 (Lu et al., 2018, 2019; 2020; Li et al., 2020; Liu and Wang, 2020a,b; Ni et al., 2018; Wang et al., 2020). Exposure to high

235   concentrations of surface ozone not only poses threat to human health, but also cause damages to crops. Previous studies have been using modelling results or observation data to study the crop production losses for single year (Lin et al., 2018; Feng et al., 2019; Zhao et al., 2020), or only focus on small regions, such as North China Plain (Hu et al., 2020; Feng et al., 2020). In this study, we applied chemical transport model simulation with updated annual anthropogenic emission inventory to study the long-term trend of O_3-induced crop production losses from 2010 to 2017 in China. This study presented a comprehensive

240   analysis on the impact of surface ozone exposure on four major crop production loss in China, including wheat, rice (double early and late rice, single rice), maize (north maize and south maize), and soybean. Emissions of major air pollutants, such as nitrogen dioxide and carbon monoxide, were seen to peak around 2012 or 2013 after China issued its first APPCAP. By looking at the trend from 2010 to 2017, we can capture the changes in crop production losses due to surface ozone exposure before and after the APPCAP. We adopted the AOT40 ozone metric (hourly ozone concentration over a threshold of 40 ppbv during

245 the growing season) and related concentration-response function (CRF) to estimate the crop production loss (CPL) and economic loss (EL), for major crops in China, including wheat, rice, maize and soybean. We first evaluated our model's performance in simulating the growing-season AOT40 in China, and found that the CAM-Chem model was underestimating the AOT40 values, with normalized mean bias ranging from -5% to -28% from 2010 to 2017, which means that the estimations for the CPL and EL in our study are conservative.

250 The annual AOT40 in China showed increasing trend since 2010, with peak in 2014, which was mainly caused by the high ozone concentration in western China. The ozone increases in mainland China were caused by a combination of unfavourable meteorological conditions, the unmitigated missions of volatile organic compounds and the decrease of $PM_{2.5}$. Spatially, the annual AOT40 values were higher in western China, North China Plain, and Yangtze River Delta, with the 8-yr annual average AOT40 highest in Xizang (41.47 ppm h), Tianjin (34.79 ppm h) and Qinghai (34.51 ppm h). However, the regions with highest

255 AOT40 values do not always have higher crops planted, such as Xizang and Qinghai, making the spatial patterns of CPL and EL significantly different from the AOT40. The growing season AOT40 values are relatively higher for wheat, north maize and soybean, showing the double-hump shape for the seasonal O_3 distribution (with growing season of March, April and May for wheat, and June, July and August for north maize and soybean). By using the CRF derived by Mills et al. (2007), we then calculated the relative yield loss (RYL) from the growing season AOT for each crop. We estimated that, at the province level,

260 the RYLs for wheat ranges from 8.13% to 25.14%, 6.72% to 10.71% for double early rice, 7.11% to 8.53% for double late rice, 6.79% to 10.22% for single rice, 0.48% to 5.29% for north maize, 0.00% to 0.94% for south maize, and 0.0% to 11.48% for soybean for the 8-yr average. The annual national average RYLs (ARYLs), which considers the fractions of the crop production loss with the hypothetical total production without ozone pollution, ranges from 11% to 22% for wheat, 8% to 9% for rice, 2% to 4% for north maize, 0% to 1% for south maize, and 1% to 3% for soybean. The estimates are comparable to

265 previous studies, such as Avnery et al (2011) reported RYLs of 3.9%-15% for wheat, 2.2% -5.5% for maize, and 8.5%-14.0% for soybean in 2000 for East Asia. Utilizing the regional CMAQ model, Lin et at. (2018) reported ozone induced RYLs between 8.5% and 14% for winter wheat, 9–15.0% for rice, and 2.2–5.5% for maize. Using national ozone monitoring network, Zhao et al. (2020) reported O_3-induced yield reductions ranging from 20.1% to 33.3% for winter wheat, 5.0—6.3% for maize, 7.3—8.8% for single rice, 3.9—6.8% for double-early rice and 5.9—7.1% for double-late rice.

270 Using the annual crop production from the Statistical Yearbook of China, we estimated that national aggregated CPL varies from 13.81 to 36.51 million Mt from 2010 to 2017 for wheat, which is comparable to the total wheat productions in Paris, the fifth largest wheat production in the world. The annual CPL for rice, including both double early and late rice, and single rice, is 16.89-20.03 million Mt, comparable to the annual rice productions in Philippines, the 8th largest rice producer in the world. The CPL for maize ranges from 4.59 to 8.17 million Mt, and 0.27 – 0.34 million Mt for Soybean. Accordingly, from 2010 to

275 2017, economic losses from surface ozone exposure ranges from 3.86 – 14.29 billion $ for wheat, 2.05 billion $ to 3.87 billion $ for double rice (with early and late rice contributes almost equally), 2.96 billion to 6.49 billion $ for single rice, 1.16 – 3.53 billion $ for maize (with north maize contributing to more than 90% of the total), and 0.16 – 0.29 billion $ for soybean. By evaluating our model's simulation with observation results, we notice that our model simulated AOT40 ozone metrics are

lower than the station observation data, which makes our estimations for the crop production and economic losses conservative.

280 Overall, from 2010 to 2017, the ozone-induced crop production loss in China is significant. The overlaps of major crop growing area, populated and industrial zones, and ozone concentration hotspots alerted the emergency of a better structured and balance control on ozone precursors to limit ozone concentration and preserve food security efficiently. The increment of ozone concentration under the scenario of stringent emission control could be attributed to the policy preference to NO_X control. Management on O_3 precursors in China was concentrated on NO_X limitation while less control was implemented on VOCs

285 (Wang et al., 2019). In the Beijing-Tianjin-Hebei Industrial Zone and the Shanghai-Nanjing-Hangzhou Economic Zone, however, VOCs' emission was a major influential factor that induced ozone generation. Correspondingly, the efficient control on particulate matters ($PM_{2.5}$ and PM_{10}) in these regions boosted photolysis rates during the formation of ozone.

Data availability. Global anthropogenic emissions data from CEDS are available from https://www.geosci-model-dev.net/11/369/2018/ (accessed May 12th, 2021). MEIC emission inventory is available from

290 http://meicmodel.org/?page_id=560 (last access May 6th, 2021). The CAM-Chem model is available at http://www.cesm.ucar.edu/models/cesm1.2/ (accessed May 12th, 2021). Data from CAM-Chem modelling that support the findings of this study are available from the corresponding author upon request.

Author contributions: YZ and DS initiated the research, and designed the paper framework. YZ ran the model, and DL processed the data, performed the data analysis and made the plots. YZ and DL analysed the results and wrote the paper, with

295 contributions from DD, XL and LZ.

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Table 1: The concentration-response function for the relative yields (RY) for ozone exposure on different crops.

Crops	concentration response function	Growing season
Wheat	RY = −0.0016×AOT40 + 0.99	MAR, APR, MAY
Rice	RY = −0.0039×AOT40 + 0.94	MAY, JUN, JUL (Double Early Rice[1])
		SEP, OCT, NOV (Double Late Rice[2])
		AUG, SEP, OCT (Single Rice)
Maize	RY = −0.0036×AOT40 + 1.02	JUN, JUL, AUG (North Maize[3])
		AUG, SEP, OCT (South Maize[4])
Soybean	RY = −0.0116×AOT40 + 1.120	JUN, JUL, AUG

[1]Double early/late rice is considered to grow in **Zhejiang, Jiangxi**, **Anhui, Hunan,** Hubei, **Fujian,** Guangdong, **Guangxi,** Hainan, **Yunnan**, Hongkong, Macao and Taiwan (Lin et al., 2019; Zhao et al., 2019).

[2]Single rice is considered to grow in Heilongjiang, Jilin, Liaoning, Hebei, Beijing, Tianjin, Shanxi, Shaanxi, Ningxia, Gansu, Xinjiang, Nei Mongol, Shanghai, Jiangsu, **Zhejiang, Anhui, Fujian, Jiangxi,** Shandong, Henan, Hubei, **Hunan, Guangxi,** Sichuan, Chongqing, Guizhou and **Yunnan** (Lin et al., 2019; Zhao et al., 2019).

[3]North maize is considered to grow in northern provinces, including Heilongjiang, Jilin, Liaoning, Beijing, Tianjin, Hebei, Henan, Shandong, Shanxi, Shaanxi, Gansu, Qinghai, Ningxia, Nei Mongol, Xinjiang and Anhui (NBSC, 2018; Zhou et al., 2019).

[4]South maize are in southern provinces only, including Shanghai, Jiangsu, Zhejiang, Fujian, Jiangxi, Hubei, Hunan, Guangdong, Guangxi, Sichuan, Chongqing, Guizhou, Xizang, Yunnan, Hainan, Hongkong, Macao and Taiwan (NBSC, 2018; Zhou et al., 2019).

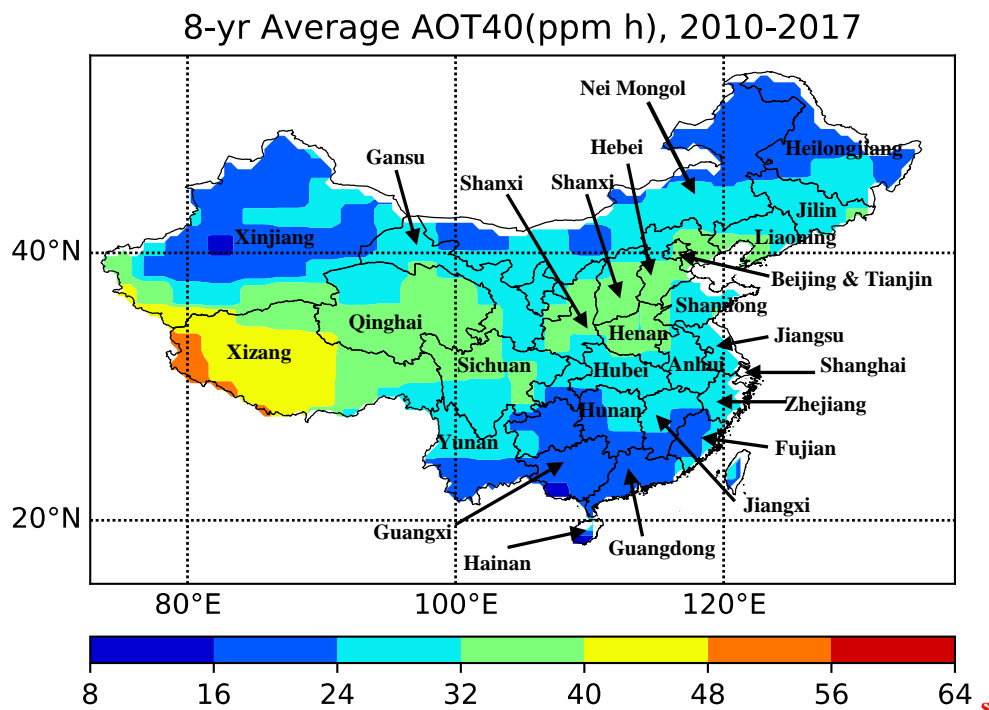



Figure 1: Spatial distribution of annual accumulated AOT40 (ppm h) in China for 8-year average (from 2010 to 2017).

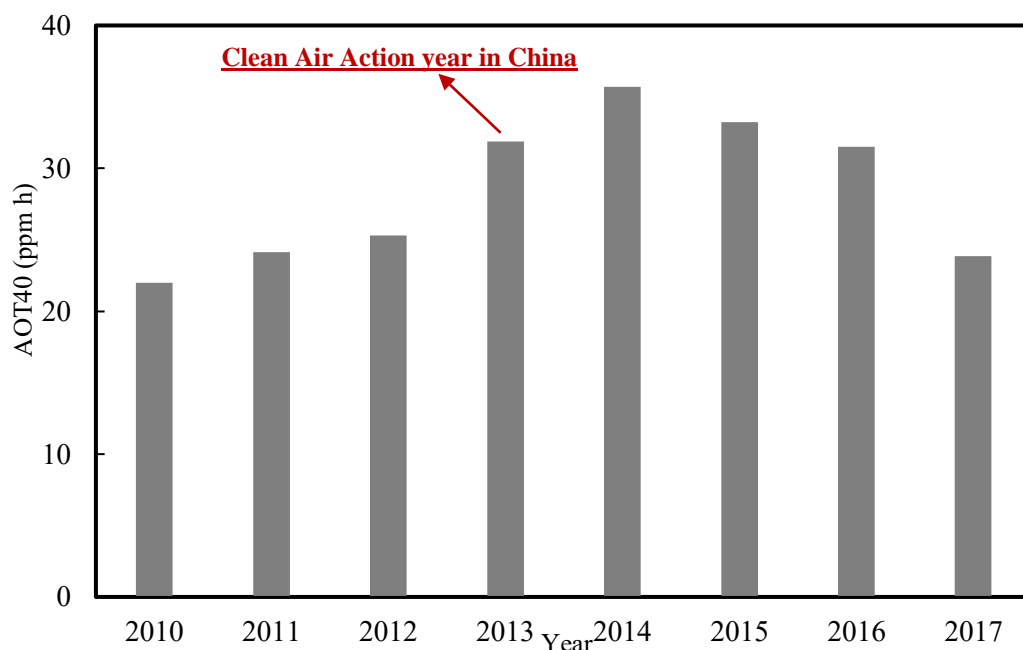



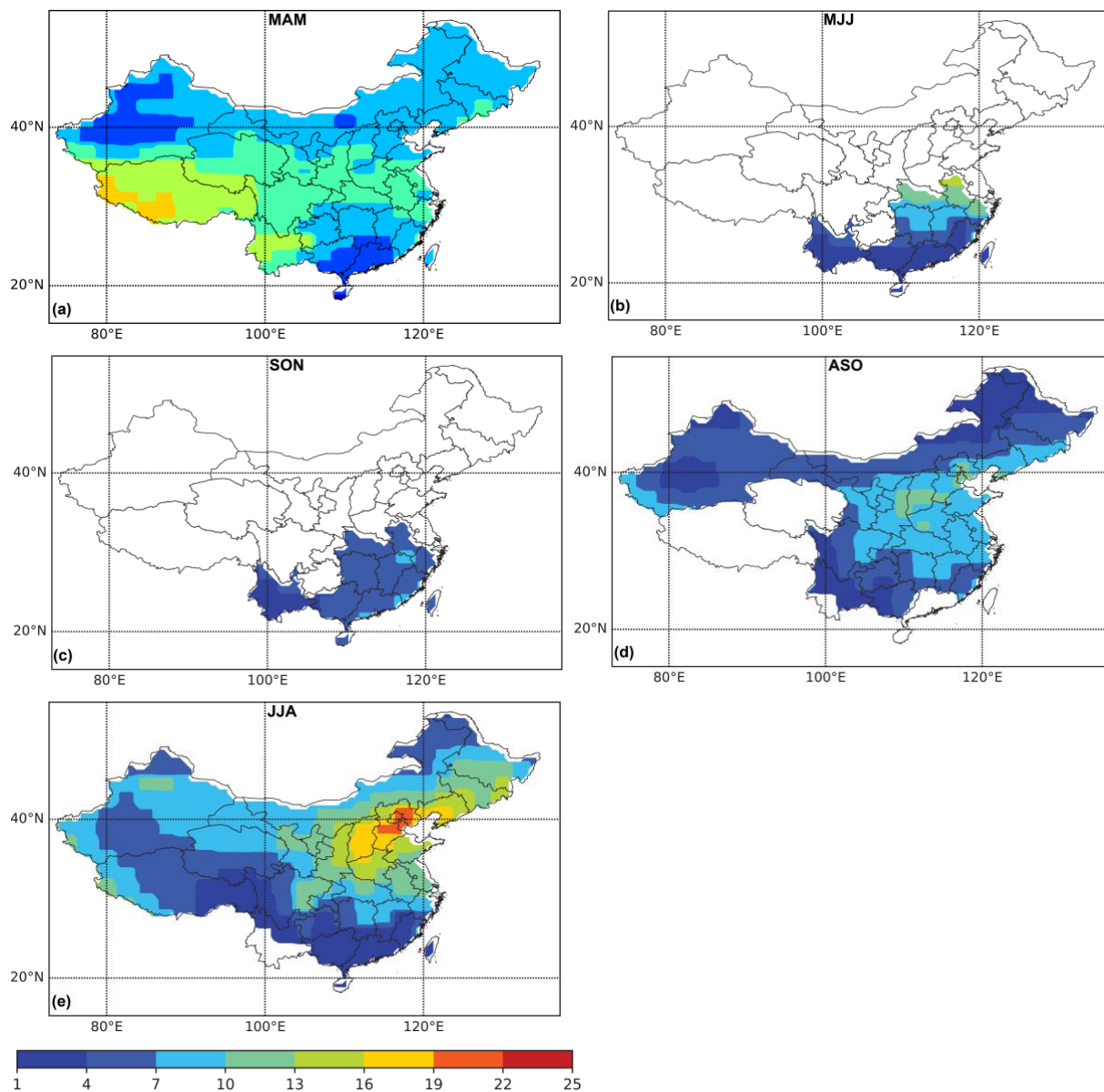
Figure 2: The national annual accumulated AOT40 values in China from 2010 to 2017. The unit is ppm h.

465

Figure 3: The spatial distribution of 8-yr average growing season accumulated AOT40 for (a) wheat, (b) double early rice, (c) double late rice, (d) single rice and south maize, and (e) soybean and north maize. The unit is ppm h.

470

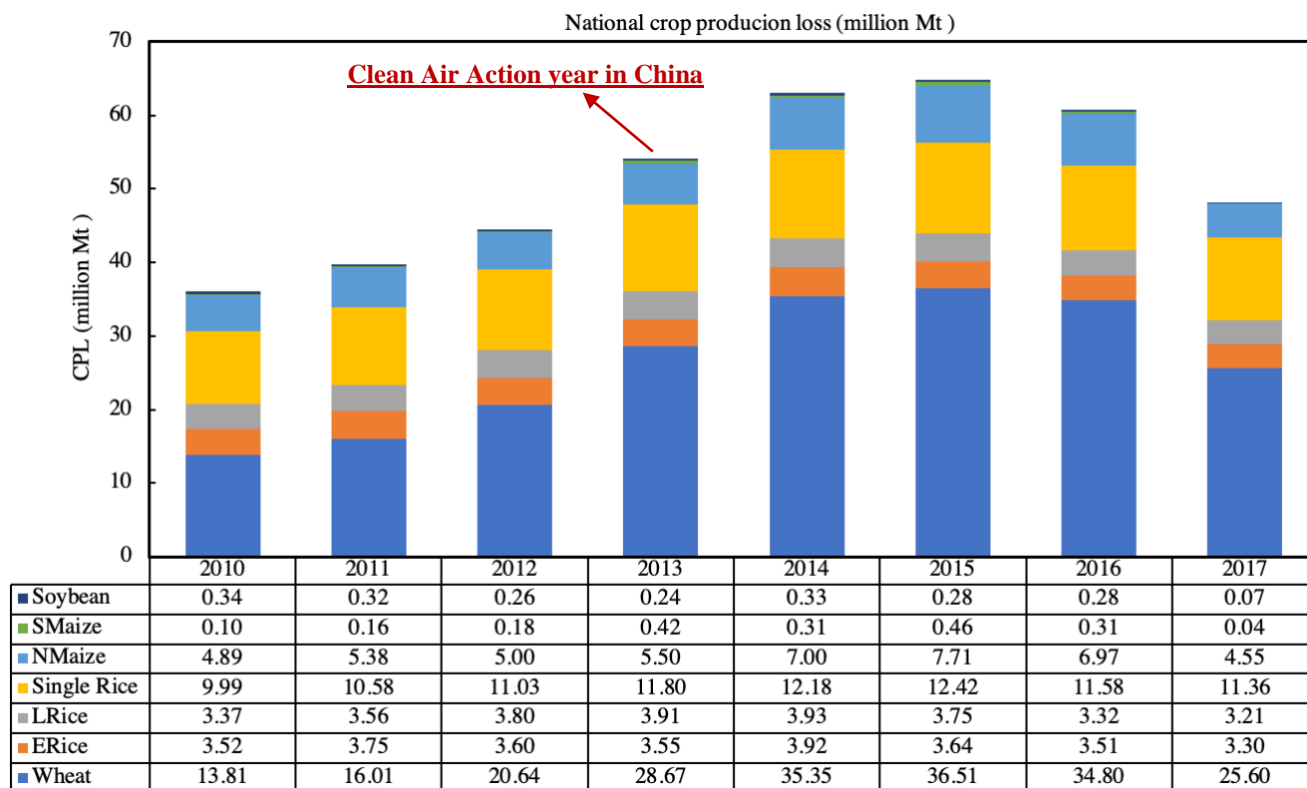



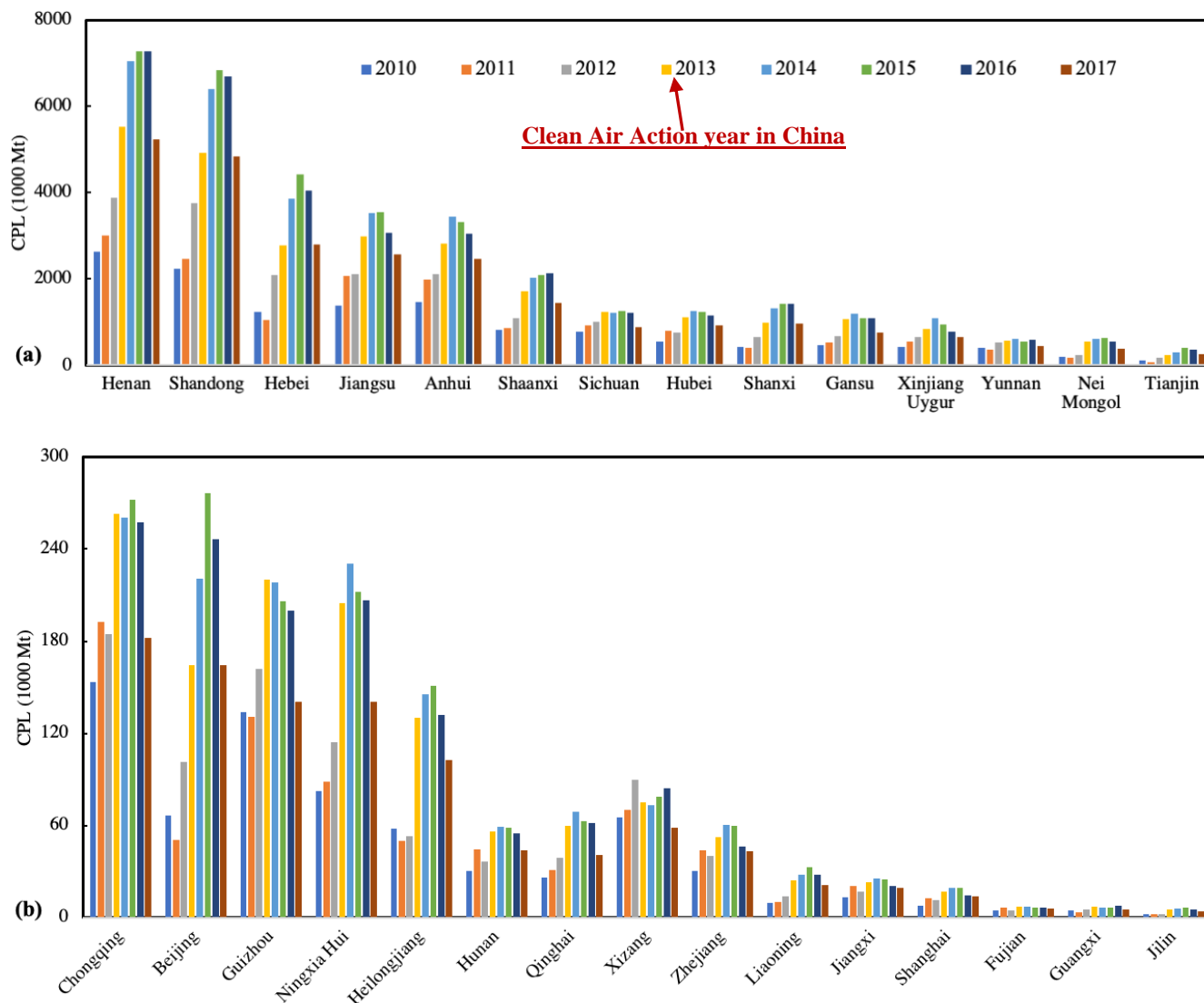
Figure 4: National crop production loss for major crops, with SMaize for south maize, NMaize for north maize, LRice for Late Rice, ERice for early rice. Unit is million metric tons.

475

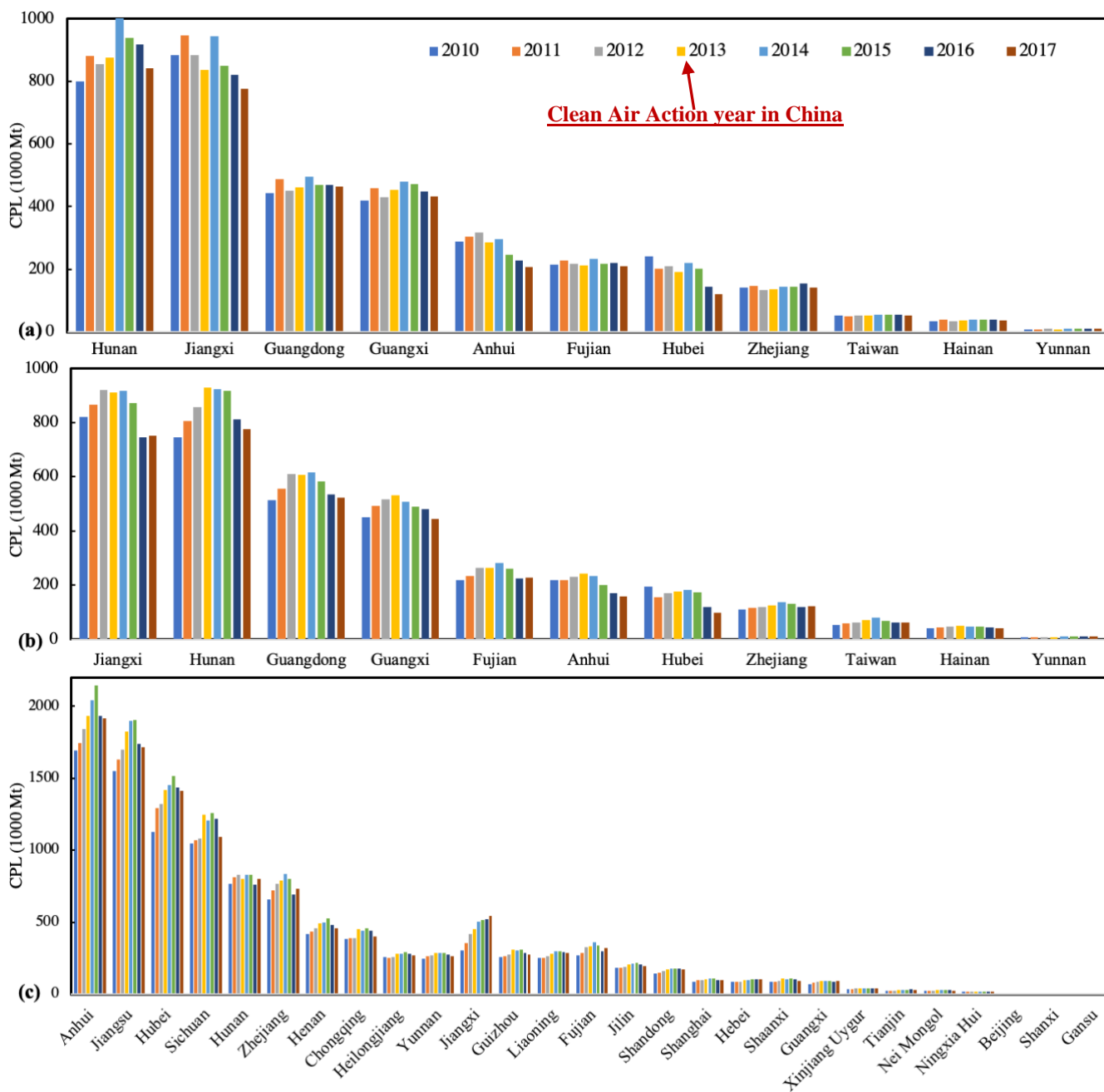
Figure 5: Annual wheat production loss by province from 2010 to 2017 (1000 Mt) due to surface ozone exposure.

480

Figure 6: The production losses for rice, including double early rice (a), double late rice (b), and single rice (c) in all the China provinces. Units of thousands Mt.

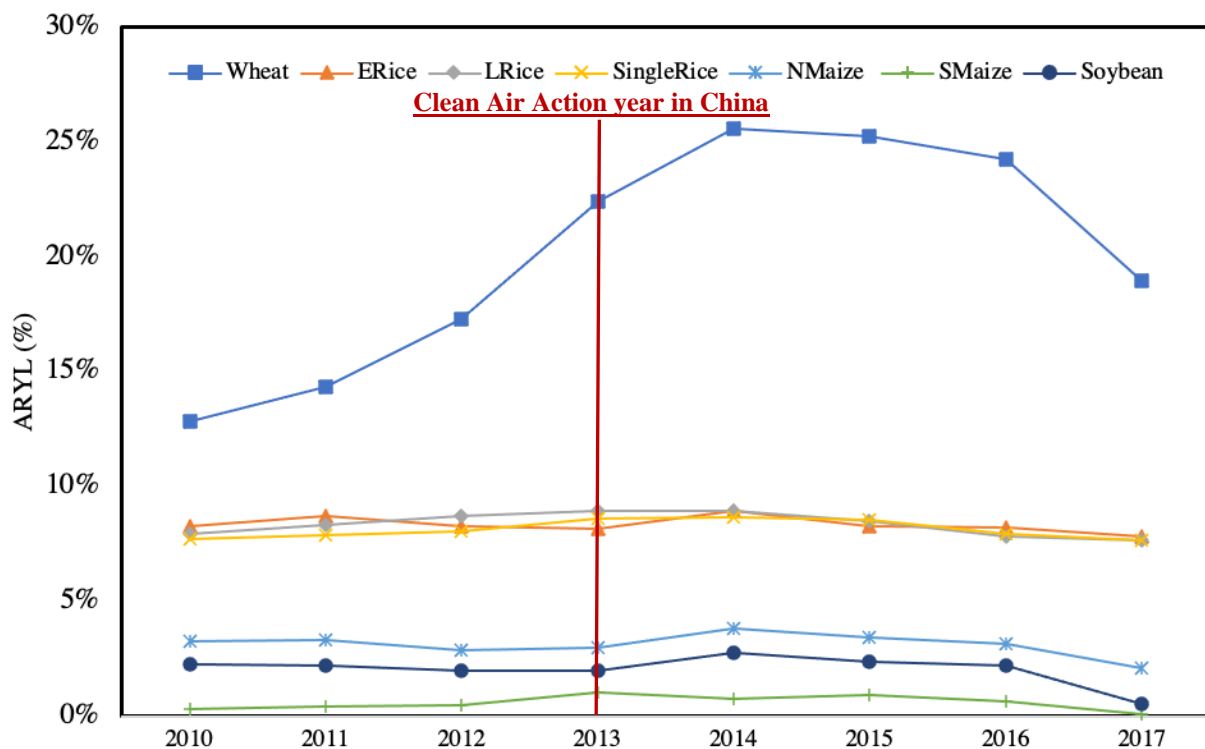



Figure 7: National average relative yield loss (ARYLs) from 2010 to 2018. The south maize (SMaize) and soybean are multiplied by
485 **10 to be comparable with other crops.**

National economics loss of wheat and rice (million USD)

(a) **Clean Air Action year in China**

Legend: ■Wheat ■ERice ■LRice ■SingleRice

	2010	2011	2012	2013	2014	2015	2016	2017
SingleRice	2964	4274	5035	5811	5577	6320	6485	5779
LRice	1001	1436	1736	1926	1800	1911	1860	1634
ERice	1045	1515	1642	1748	1794	1853	1965	1677
Wheat	3860	5147	6672	10179	13328	14292	13401	9842

(b) **Clean Air Action year in China**

Legend: ■NMaize ■SMaize ■Soybean

	2010	2011	2012	2013	2014	2015	2016	2017
Soybean	251	256	220	160	291	224	162	55
SMaize	27	51	68	205	137	198	82	11
NMaize	1336	1731	1917	2689	3092	3332	1842	1147

Figure 8: National economic loss from cop production loss from wheat and rice (double early & late rice, single rice) (a), and maize (north maize and south maize), and soybean (b) from 2010 to 2017. The units are million USD.

490