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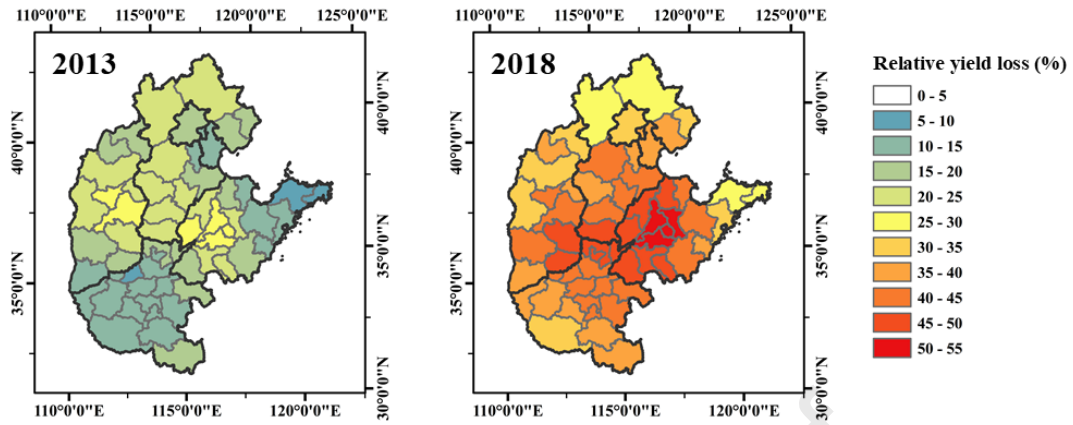
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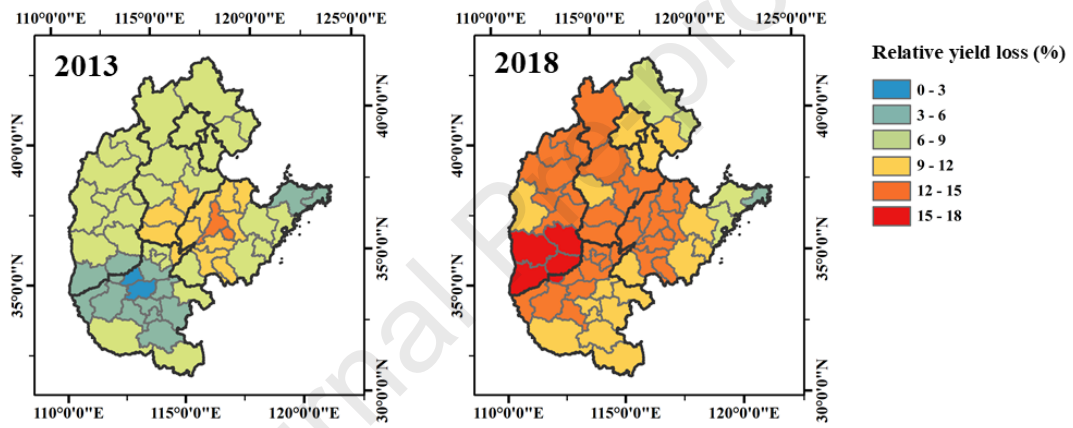
Can Dong: Conceptualization, Methodology, Software, Writing. **Rui Gao:** Resources, Review & Editing. **Xin Zhang:** Visualization. **Hong Li:** Review & Editing. **Wenxing Wang:** Review & Editing. **Likun Xue:** Review & Editing, Supervision.

Journal Pre-proof

Wheat



Maize



1 **Assessment of O₃-induced crop yield losses in northern China** 2 **during 2013-2018 using high-resolution air quality reanalysis data**

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8 **Abstract**

9 Long-term exposure of food crops to high concentrations of ambient ozone (O₃) can cause
10 significant yield reductions. O₃-induced crop loss studies are limited in China, especially in the
11 North China Plain (NCP) where agricultural resources are abundant and O₃ concentrations are
12 high. In this study, we quantify the O₃-induced adverse impacts on wheat and maize over the
13 NCP and Shanxi province during 2013-2018 through the use of high-resolution air quality
14 reanalysis dataset and land-use dataset. Results show that the accumulated hourly O₃
15 concentration above 40 ppb (AOT40) in croplands experienced an upward trend, with an
16 annual increase of 2.2 ppm h (18.1%) during the wheat growing period and 1.5 ppm h (10.9%)
17 during the maize growing period from 2013 to 2018. O₃-induced relative yield losses grew
18 from 17.9% in 2013 to 38.6% in 2018 for wheat, and ranged from 7.5-11.9% for maize. The
19 estimated crop production losses also increased over time. Shandong and Hebei provinces are
20 the hot spots of crop losses and priorities should be given to them for O₃ pollution prevention.
21 Comparison with previous studies shows that uncertainties still exist in crop loss estimations.
22 More rural O₃ measurements and localized crop exposure-response experiments should be
23 performed for better assessments.

24 **Keywords:** crop yield losses, ozone, North China Plain

25

26 **1. Introduction**

27 China has nearly 20% of the world's population, but less than 10% of its arable land. Due
28 to rapid economic/population growth, rising living standards and land scarcity, China has
29 become the world's largest agricultural importer
30 ([https://www.fas.usda.gov/data/china-evolving-demand-world-s-largest-agricultural-import-](https://www.fas.usda.gov/data/china-evolving-demand-world-s-largest-agricultural-import-market)
31 [market](https://www.fas.usda.gov/data/china-evolving-demand-world-s-largest-agricultural-import-market), access date 5 December 2020). Motivated by food security and other concerns, China
32 has a long-standing grain self-sufficiency policy, i.e. satisfying a minimum of 95% of national
33 demand of major staple crops (rice, wheat and maize) through domestic production (State
34 Council of China, 1996). In 2019, China produced 17.4% of the world's wheat and 22.7% of
35 the world's maize (data retrieved from <http://www.fao.org/faostat/en/#data/QC>, access date 5
36 December 2020). With China's limited agricultural land resources, achieving greater yields on
37 existing croplands is thus essential to preserve self-reliance with the growing food demand.

38 Tropospheric ozone (O_3), an important greenhouse gas and a strong atmospheric oxidant,
39 is ubiquitous in the air. Ground-level O_3 can harm both human health and vegetation (Booker et
40 al. 2009, Cohen et al. 2017, Jerrett et al. 2009). The O_3 -associated losses of crops based on
41 chamber or field studies have been reported in US, Europe, China, India and many other
42 countries (Emberson et al., 2009; Feng et al., 2015; Mills et al., 2011; Pleijel et al., 2019; Wang
43 et al., 2012). These studies revealed that long-term exposure of crops to high concentrations of
44 O_3 (e.g., >40 ppb for an hour) during the growing seasons has a cumulative effect, leading to
45 yield reductions. Troposphere O_3 is formed by the photochemical reactions of nitrogen oxides
46 ($NO_x = NO + NO_2$) with carbon monoxide (CO), methane (CH_4), and volatile organic
47 compounds (VOCs) (Wang et al., 2017). Since 1990s, concentrations of O_3 precursors in
48 Europe and North America have shown a downward trend due to the implementation of
49 emission reduction policies, leading to lower O_3 levels (Monks et al., 2015). In contrast, in Asia,
50 particularly in China, the surface O_3 concentrations have undergone a significant increase in
51 recent years (Li et al., 2016; Lu et al., 2018; Monks et al., 2015; Sun et al., 2016; Sun et al.,
52 2019; Wang et al., 2009; Xue et al., 2014). Accordingly, the impacts of O_3 pollution are
53 expected to worsen in China and special attention should be paid to assess the potential effects
54 of O_3 on crop losses.

55 Using experimentally derived exposure-response (ER) functions, numerous studies have
56 been performed to assess the crop yield losses at the global or regional scale. A recent study by
57 Schauburger et al. (2019) examined the global historical (between 2008 and 2010) soybean and
58 wheat relative yield losses (RYL) from O_3 pollution with consideration of the modifying

59 effects of water and temperature. They reported that global soybean losses varied between 2%
60 and 10% for different countries; European/North American wheat losses varied between 0%
61 and 27%; Asian wheat losses ranged from 4% to 39%. Using different methods, Seltzer et al.
62 (2020) assessed the long-term impacts of O₃ on agriculture over continental US and found
63 improvements of crop (maize, soybeans and wheat) yields, with RYL values dropping from 3.4%
64 (or 4.6%), 11.9% (or 16.3%) and 12.1% in 2000 to 1.6% (or 2.9%), 4.8% (or 11.2%) and 9.4%
65 in 2015, respectively. Sharma et al. (2019) estimated that O₃ led to 21% RYL for wheat and 6%
66 RYL for rice in year 2014-2015 in India. Tang et al. (2013) estimated that in the year 2000, the
67 RYL of wheat caused by O₃ in China and India were 6.4–14.9% and 8.2–22.3%, respectively.
68 Overall, estimation of losses from these studies indicates that impacts of O₃ exposure on crop
69 yields are higher in Asia than in US and Europe.

70 In the context of the growing food demands and worsening ozone pollution in China, the
71 demand for quantifying ozone-associated RYL increases. A few studies specifically estimated
72 O₃-attributed crop yield reductions in China but presented quite different results. For example,
73 RYL of wheat induced by O₃ in 2015 were estimated to be as low as 6% to as high as 33.3%
74 (Feng et al., 2019a; Feng et al., 2020; Hu et al., 2020). The large uncertainties are mainly
75 introduced by the estimate of O₃ exposure and the choice of the E-R function. First, O₃
76 exposure estimation can rely on observational or model-simulated data. There are pros and
77 cons of each method. While measurements reflect the real concentration of air pollutants at the
78 monitoring site, they have a limited coverage of space and time, masking the spatiotemporal
79 variability of O₃. One relevant issue is that if most of the air quality monitoring stations are
80 located in cities, measured data may not be representative of the pollution level in the rural
81 areas where the crops are planted. As an alternate data source for the O₃ exposure calculation,
82 air quality modeling data are not limited by time or space, but suffer uncertainties from the
83 spatial resolution, meteorology, emission inventory, chemical mechanisms, etc. Second, E-R
84 functions derived for a certain food crop can differ significantly under influences of different
85 climate types and crop genotypes. For example, Schauburger et al. (2019) reported that Asian
86 crops are more vulnerable to O₃ pollution compared to crops in US or Europe. Such differences
87 influence the assessment and may lead to great discrepancies in the crop loss estimates.

88 In this study, we aim to determine more accurately the threat of O₃ pollution on crops by
89 using a high spatial resolution (15 × 15 km) air quality reanalysis dataset that optimally
90 combines the observations with air quality forecasts through data assimilation, a high
91 resolution (1 × 1 km) land use dataset (for identifying locations of croplands), E-R functions

92 derived for crops grown in China, and city-level crop yields data. The study area of this work,
93 where agriculture is a major source of livelihood for rural communities (Fig. S1), covers the
94 North China Plain (NCP) region (i.e., Beijing, Tianjin, Hebei province, Henan province, and
95 Shandong province), and Shanxi province. Figure 1 shows ozone concentrations are high in
96 this area during the warm seasons. According to the Statistical Yearbook of China
97 (<http://www.stats.gov.cn/tjsj/ndsj/>, last access: 5 December 2020), in 2019, this area produced
98 8.05×10^7 ton wheat and 7.85×10^7 ton maize, accounting for 60.2% and 30.1% of the national
99 total production, respectively. Consequently, a better understanding of O₃-induced crop losses
100 in this area is of great significance. This work assesses the O₃-related yield and economic
101 losses from a relatively long-term perspective (2013-2018) and results from this study improve
102 over previous studies by incorporating locally derived E-R relationships of crops with air
103 pollutant data that are superior (by using reanalysis data and considering the variations of O₃
104 concentrations in crop growing areas at a fine scale) to both measurements and model
105 simulations.

106 **2. Methodology**

107 **2.1 Data sources**

108 Hourly surface O₃ concentration data over the study area spanning 2013-2018 were
109 obtained from the Chinese Air Quality Reanalysis dataset (CAQRA) (Tang et al., 2020). This
110 dataset was produced by the chemical data assimilation system (ChemDAS, developed by the
111 Institute of Atmospheric Physics, Chinese Academy of Sciences) which assimilates surface air
112 quality observations from China National Environmental Monitoring Center based on the
113 ensemble Kalman filter (the assimilation algorithm) and the Nested Air Quality Prediction
114 Modeling system (a three dimensional chemical transport model). Surface concentrations of
115 six air pollutants (PM_{2.5}, PM₁₀, NO₂, SO₂, CO and O₃) are provided at high spatial (15 × 15 km)
116 and temporal (1 hour) resolutions. Comparisons with observations from over 1000 air quality
117 monitoring stations and the Copernicus Atmosphere Monitoring Service reanalysis dataset
118 (produced by the European Centre for Medium-Range Weather Forecasts) show that CAQRA
119 has excellent performance in reproducing the spatiotemporal variations of surface
120 concentrations of air pollutants. Detailed descriptions of this dataset can be found in Kong et al.
121 (2021).

122 The land use data (1×1 km resolution) for 2015 were downloaded from the Resource and
 123 Environment Science and Data Center (<http://www.resdc.cn/>, last access: 5 December 2020).
 124 According to the Statistical Yearbook of China (<http://www.stats.gov.cn/tjsj/ndsj/>, last access:
 125 5 December 2020), the total area of the cropland in China was 240, 000 km² in 2013 and 236,
 126 000 km² in 2018. Thus we assume locations of the cropland grid cells in the land use dataset
 127 remain unchanged during 2013-2018 and crops (wheat and maize) are cultivated in those grid
 128 cells.

129 Yields of wheat and maize in 59 cities of the study area were obtained from the Statistical
 130 Yearbook of China (2013-2018). Locations and names of the cities can be found in Figure S1
 131 and Table S1. The annual purchase prices of wheat and maize (listed in Table S2) in China
 132 were compiled by the Food and Agriculture Organization of the United Nations (FAO)
 133 Statistical Database (<http://www.fao.org/faostat/>, last access: 5 December 2020).

134 2.2 AOT40 calculation

135 We use the AOT40 (accumulated hourly O₃ concentration above 40 ppb, Eq. 1), an
 136 exposure index that is widely used by the ozone research community, for the assessment of the
 137 potential risk of ambient O₃, for estimations of yield losses of winter wheat and summer maize
 138 (Paoletti et al. 2007). The accumulation periods for wheat and maize are defined as April 1 to
 139 June 15 (springtime) and July 1 to September 30 (summertime), respectively.

$$140 \quad \text{AOT40}(\text{ppm h}) = \sum_{i=1}^n ([\text{O}_3]_i - 40) / 1000, \text{ for } \text{O}_3 \geq 40 \text{ ppb} \quad \text{Eq. 1}$$

141 Where, $[\text{O}_3]_i$ is the hourly O₃ concentration in ppb during the daytime hours (between 8:00 and
 142 18:00 of China Standard Time); n is the number of hours over the crop growing season.

143 AOT40 calculation was performed using the air quality reanalysis dataset. Next, AOT40
 144 data were re-gridded to 1×1 km horizontal resolution with the Kriging interpolation method
 145 using the ArcMap (version10.7) software to match the resolution of the land use data. Then
 146 AOT40 values in the cropland grid cells were extracted. Finally, the extracted AOT40 data
 147 were averaged at the city level using the Spatial Analyst Tool of ArcMap for crop loss
 148 estimates.

149 2.3 Crop relative yield and economic loss estimation

150 Relative yields (RY) were estimated using the E-R functions derived for wheat (Zhu et al.,
 151 2011) and maize (Peng et al., 2019) in China.

152 For wheat:

$$153 \quad RY = -0.0205 \times AOT40 + 1 \quad \text{Eq. 2}$$

154 For maize:

$$155 \quad RY = -0.00577 \times AOT40 + 1 \quad \text{Eq. 3}$$

156 Equations 4-6 were used to calculate the relative yield losses, crop production losses (CPL),
157 and economic cost losses (ECL) for each city:

$$158 \quad RYL = 1 - RY \quad \text{Eq. 4}$$

$$159 \quad CPL = CP \times RYL / (1 - RYL) \quad \text{Eq. 5}$$

160 Here CP is the wheat/maize production obtained from the Statistical Yearbook.

$$161 \quad ECL = CPL \times MPP \quad \text{Eq. 6}$$

162 Where, MPP stands for the annual purchase price of wheat/maize (Table S2).

163 **3. Results and Discussion**

164 **3.1 Magnitudes of AOT40**

165 **3.1.1 AOT40 during the growing period of wheat**

166 Table 1 summarizes the regional mean, maximum and minimum values of springtime
167 AOT40 for each year. The average AOT40 over the study area had increased from 8.5 ppm h in
168 2013 to 19.4 ppm h in 2018, with an annual increase of 2.2 ppm h (18.1% growth per year).
169 Moreover, O₃ exposure increased drastically (by 33.3%) from 2016 to 2017. This upward trend
170 of O₃ exposure is in general consistent with the worsening O₃ pollution in the NCP region (Sun
171 et al., 2016), and demonstrates the growing risks for winter wheat.

172 Figure 2 shows the gridded spatial distributions of AOT40 over the croplands during the
173 growing period of wheat for each year. It is apparent that springtime AOT40 featured
174 significant increases throughout the study period. In 2013, values of AOT40 in most of the
175 cropland grid cells were below 15 ppm h. In comparison, in 2017 and 2018, AOT40 in more
176 than half of the croplands were greater than 15 ppm h. On an annual basis, higher levels of
177 AOT40 were distributed in the intensively farmed areas (i.e., the central part of the study area).
178 Specifically, for all years, cities in the west of Shandong province and southeast of Hebei
179 province suffered from relatively high AOT40, indicating elevated risks for wheat grown in

180 those regions. Substantial increases of AOT40 also occurred over the northern part of Henan
181 province from 2016 to 2018, and the widespread O₃ pollution would put more vegetation under
182 greater risks.

183 3.1.2 AOT40 during the growing period of maize

184 The regional mean, maximum and minimum values of summertime AOT40 from 2013 to
185 2018 can be found in Table 1. In general, similar to that of springtime AOT40, summertime O₃
186 exposure also exhibited an upward trend. The average values of AOT40 over the study area
187 during the maize growing period ranged from 13.1 ppm h to 22.0 ppm h, with an increase rate
188 of 1.5 ppm h (10.9%) per year from 2013 to 2018. It should also be noted that summertime
189 AOT40 peaked and experienced the fastest rate of increase in 2017, which was a 31.0%
190 increase compared to the average value in 2016 (16.8 ppm h). Meanwhile, O₃ exposure
191 decreased by 6.3% from 2017 (22.0 ppm h) to 2018 (20.6 ppm h). If 2018 had been excluded,
192 the average increase of regional mean AOT40 (2013 - 2017) per year would be 2.2 ppm h,
193 which was the same as that of the springtime AOT40. While the estimated O₃ exposure was
194 higher in the summertime (Table 1, Figs. 2 and 3), the percentage increase rate of AOT40
195 during the growing period of wheat was faster than that during the growing period of maize.
196 Considering the fact that wheat is less O₃-tolerant than maize in chamber/field studies (Zhu et
197 al., 2011; Peng et al., 2019), yield reductions of winter wheat are expected to be higher than
198 those of summer maize. This will be discussed in Section 3.2.

199 Figure 3 presents the gridded spatial distributions of AOT40 over the croplands during the
200 growing period of maize for each year. Though summertime AOT40 experienced an overall
201 increase from 2013 to 2018, the changes were somewhat inhomogeneous. Being the hot spots
202 of O₃ pollution, AOT40 in certain areas of Shandong and Hebei provinces did not show
203 consistent increases over time. The 2014, 2015 and 2018 AOT40 in some regions were lower
204 than values in 2013, 2014 and 2017, respectively (see blue circles in Fig. 3). The substantial
205 variations of AOT40 indicate the necessity of the use of high-resolution O₃ data for crop loss
206 estimation. Figure 3 also shows that prior to 2016, most parts of Shanxi and Henan provinces
207 had relatively low O₃ exposure (< 15 ppm h). In contrast, for 2017 and 2018, the majority of
208 AOT40 exceeded 20 ppm h, and some extremely high values occurred near the borders of
209 Shanxi and Henan provinces. Such widespread increase of O₃ exposure would affect more
210 crops and lead to more yield reductions.

211 3.2 Estimation of crop yield and economic losses

212 Because the relative yield losses and AOT40 are linearly related (see Equations 2-4), their
 213 spatial and temporal distributions are expected to be similar. Meanwhile, crop production
 214 losses are dependent upon both relative yield losses and crop production; economic cost losses
 215 are functions of both crop production losses and the purchase price. In the following section,
 216 the O₃-associated yield and economic cost losses for winter wheat and summer maize will be
 217 discussed separately.

218 3.2.1 Yield and economic cost losses of winter wheat

219 As shown in Figure 4, the city-specific RYL of wheat due to O₃ exposure increased
 220 substantially over the study period. The spatial averages of RYL over the study area were
 221 17.9%, 21.4%, 23.6%, 27.6%, 35.9% and 38.6% for 2013, 2014, 2015, 2016, 2017 and 2018,
 222 respectively. The regional highest RYL (2013: 28.2% in Laiwu; 2014: 35.3% in Weifang; 2015:
 223 33.8% in Linyi; 2016: 37.1% in Laiwu; 2017: 47.1% in Jincheng of Shanxi province, but 46.1%
 224 in Tai'an; 2018: 52.2% in Ji'nan) kept occurring in cities of Shandong province. The
 225 widespread and intense impacts of O₃ pollution on winter wheat were most apparent in 2017
 226 and 2018, with most cities (84.7% in 2017 and 89.8% in 2018) suffering more than 32% of
 227 yield losses. In 2018, the estimated RYL in cities in the west of Shandong (i.e., Binzhou,
 228 Dezhou, Zibo, Ji'nan, Tai'an, Laiwu, Liaocheng and Ji'ning) were close to 50%, indicating
 229 serious threats for wheat from O₃ pollution. The lowest value of annual RYL for wheat also
 230 increased over time, and these estimated minimum values occurred in cities near the
 231 boundaries of the study area (i.e., 8.8% in Weihai and Yantai in 2013, 9.2% in Yangquan in
 232 2014, 13.2% in Linfen in 2015, 16.5% in Yuncheng in 2016, 24.3% in Chengde in 2017 and
 233 26.1% in Zhangjiakou in 2018).

234 City-level production losses of winter wheat are presented in Figure 5. Cities with high
 235 CPL were mostly located in the main wheat production region (Shandong, Henan and Hebei
 236 provinces). CPL increased drastically over time. Estimated total CPL in 2013, 2014, 2015,
 237 2016, 2017 and 2018 were 1632.0×10^4 , 2301.6×10^4 , 2728.2×10^4 , 3161.6×10^4 , 5064.0×10^4 , and
 238 5885.7×10^4 tons, respectively, amounting to 13.2%, 17.9%, 20.6%, 23.7%, 37.7% and 44.8%
 239 of the national wheat production of the respective year. It should be emphasized that this area
 240 is the major wheat production region in China, which contributes to the majority (e.g., 60.2% in
 241 2019) of national wheat production. Calculated annual total ECL (based on Eq. 6 and Table S2)
 242 and losses as a percent of China gross domestic product (GDP, obtained from the Statistical
 243 Yearbook) are shown in Figure 8(a). O₃-related economic losses increased remarkably during

244 the study period. The ECL of wheat in 2018 was 20.1 billion USD or 132.7 billion CNY
245 (representing 0.144% of 2018 GDP), which was 3.7 times of the economic loss in 2013.

246 **3.2.2 Yield and economic cost losses of summer maize**

247 The city-level relative yield losses of maize due to O₃ exposure are shown in Figure 6. The
248 spatial averages of RYL over the study area were 7.5%, 8.3%, 8.5%, 9.4%, 12.8% and 11.9%
249 for 2013, 2014, 2015, 2016, 2017 and 2018, respectively. These values were much lower than
250 the estimated mean RYL for wheat, reflecting that maize was less affected by O₃ pollution.
251 Like the summertime AOT₄₀, RYL of maize were greatest in 2017 (the estimated RYL in 44
252 out of 59 cities exceeded 12%). The largest RYL of maize occurred in Shandong province in
253 2013 (12.9% in Laiwu), 2014 (13.8% in Weifang) and 2016 (12.4% in Dezhou), but in Shanxi
254 province in other years (12.8% in Shuozhou in 2015, 17.3% in Jincheng in 2017, and 16.3% in
255 Jincheng in 2018). Meanwhile, the estimated lowest RYL value for each year occurred in cities
256 of different provinces (i.e., 2.3% in Jiaozuo in 2013, 4.1% in Linfen in 2014, 4.3% in
257 Yangquan in 2015, 4.7% in Jincheng in 2016, 6.6% in Xinyang in 2017, 5.2% in Weihai in
258 2018). Variations of the temporal distributions of RYL in spring and summer indicate the
259 seasonal differences of O₃ pollution characteristics.

260 The city-level production losses of maize are presented in Figure 7. Cities with higher CPL
261 were mostly located in Shandong and Hebei provinces for all years, and also in Shanxi and
262 Henan provinces since 2016. The estimated total CPL in 2013, 2014, 2015, 2016, 2017 and
263 2018 were 670.6×10^4 , 725.2×10^4 , 713.7×10^4 , 822.3×10^4 , 1140.9×10^4 , and 1095.8×10^4 tons,
264 respectively, accounting for 2.7%, 2.9%, 2.7%, 3.1%, 4.4% and 4.3% of the national maize
265 production in the respective year. The purchase prices of maize were less stable than those of
266 wheat, leading to larger variations of ECL. Figure 8(b) shows that 2016 had the minimum ECL,
267 which can be explained by the low purchase price of maize in that year (only 264 USD/ton
268 compared to more than 370 USD/ton in other years as listed in Table S2). The highest ECL of
269 maize occurred in 2018 (4.36 billion USD or 28.9 billion CNY), amounting to 0.031% of
270 China GDP in the same year.

271 **3.3 Comparison of RYL with other studies and recommendations**

272 Estimated crop losses may differ as a result of differences in estimated O₃ exposure, use of
273 different E-R equations, as well as different estimation units (county-level, province-level,
274 city-level, etc.). To place our results in a broader context, Table 2 and 3 summarize the results
275 from recent studies that focus on assessments of O₃-induced crop losses on the regional scale. It

276 is apparent that except for Feng et al. (2019a), the estimated RYL of wheat/maize for recent
277 years by other Chinese and Indian studies are significantly higher than those in US. Being the
278 top two most populous countries in the world, reducing O₃ pollution would not only increase
279 the crop yields, but also decrease related health risks.

280 The estimated AOT40 and RYL from this work are in general within the range of values
281 reported by other Chinese studies. Calculated annual increase rates of AOT40 during the wheat
282 growing period in this study, Zhao et al. (2020) and Hu et al. (2020) are quite close, with the
283 respective values of 2.2, 2.1, and 2.0 ppm h yr⁻¹, though variations of same year AOT40 are
284 large. AOT40 estimations are dependent on both O₃ data source and the assumed crop growth
285 period. Higher daytime O₃ concentrations and longer accumulation periods would lead to an
286 increase in AOT40 and thus higher RYL using the same E-R equation. Taking the year 2015
287 for example, the reported lowest RYL for wheat was 6% in Feng et al. (2019a), and the highest
288 value was 22.7% in Hu et al. (2020). As the two studies both used observations as the O₃ data
289 source, the RYL discrepancy may be caused by the accumulation period differences. The other
290 reason might be that the former study focused on the national RYL, while the latter focused on
291 the NCP area where O₃ levels were high. This point of view is supported by Zhao et al. (2020),
292 who reported 33.3% national RYL in 2018, but much higher RYL in polluted areas (Hebei:
293 55.3%, Shandong: 48%, Henan: 50.9%, Shanxi: 49.9%).

294 Table 2-3 show definitions of crop growing seasons in different studies vary significantly.
295 To investigate the influences of the accumulation period, we calculated AOT40 based on
296 different accumulation periods and results for RYL are listed in (Table S3). For wheat, an
297 earlier start time of the growing period results in lower levels of O₃ exposure. This is expected
298 because O₃ concentrations are lower in March than in the warmer months. Assuming the start
299 date to be March 10, RYL of 2018 wheat was estimated to be 26.9%, which is significantly
300 lower than 38.6% (RYL assuming the start date to be April 1). For maize, an earlier start time
301 of the growing period leads to higher estimated levels of O₃ exposure. Assuming the start date
302 to be June 1, RYL of 2018 wheat was estimated to be 16.7%, which is higher than 12.8% (RYL
303 assuming the start date to be July 1). Variations of RYL for maize associated with changes of
304 the growing period are smaller than those for wheat, due to the crop-sensitivity differences to
305 O₃ exposure. Our results indicate the start, end dates and duration of the crop growth periods
306 can impact RYL estimations significantly and highlight the importance of crop phenology data
307 for better assessments.

308 The estimated losses can differ significantly due to the selection of E-R functions as well.
309 Results from Lin et al. (2018) indicate that by adopting different E-R equations, the calculated
310 RYL for both wheat and maize varied by almost a factor of 2. This emphasizes the need to
311 derive localized O₃ exposure and crop yield relationships that are suitable for use in specific
312 climates of China.

313 It is not straight forward to compare results from this work with Hu et al. (2020) and Feng
314 et al. (2020), because of differences in O₃ data source and the assumed crop growth period,
315 both of which can affect RYL remarkably. Though results differ, all studies found rising levels
316 of O₃ exposure and decreases in crop yields. In future, more O₃ measurements in the rural areas
317 are required to improve the future estimates of crop losses, in view of the fact that the existing
318 air quality monitoring network is mainly established in urban areas in China.

319 Despite the high uncertainties in existing estimations of O₃-induced crop losses, we
320 provide recommendations for reducing O₃ adverse impacts on the basis of the evolution of
321 AOT40 during the crop growing seasons. As shown in Figure 9(a), AOT40 rose faster in the
322 late growing period of winter wheat. In 2017 and 2018, accumulated O₃ exposure in the last 7
323 days (from to June 9 to June 15) were 2.67 and 2.80 ppm h, respectively, leading to more than
324 5% estimated relative yield losses. This indicates at current O₃ levels, the timely harvest of
325 wheat can help reduce O₃ exposure and minimize the losses. Figure 9(b) shows AOT40
326 increased steadily during the maize growing period, but with a slower rate in late September.
327 Thus, optimizing the sowing date of maize towards sowing at a later time, may help increase
328 crop yields. Nevertheless, it is important to remember that our suggestions are made to reduce
329 the O₃-related crop losses by avoiding high O₃ days. The time of sowing and harvesting is
330 typically determined by local meteorological conditions (such as sunlight, temperature, and
331 precipitation), and changing this time window might not be realistic and would probably also
332 induce yield losses. In the long term, O₃ pollution mitigation is the most meaningful way to
333 minimize crop losses.

334 **4 Conclusions**

335 In this study, we estimated the relatively long-term (2013-2018) city-level threat of O₃ air
336 pollution on winter wheat and summer maize in the North China Plain by using an air quality
337 reanalysis data set that are superior to both measured and model simulated O₃ data (method
338 used by previous studies), a high resolution land use data set (not considered by previous
339 studies), and E-R functions derived for crops in China. The main conclusions are as follows.

340 1. The O₃ exposure (AOT40) showed a significant upward trend from 2013 to 2018 in the
341 study area, with an annual increase of 2.2 ppm h (18.1%) during the wheat growing period
342 (springtime) and 1.5 ppm h (10.9%) during the maize growing period (summertime). In general,
343 AOT40 exhibited an upward trend in both seasons, and increased faster in spring.

344 2. The O₃-induced relative yield losses increased from 17.9% in 2013 to 38.6% in 2018 for
345 winter wheat, and ranged from 7.5-11.9% for summer maize. The estimated crop production
346 losses also increased with time. Special attention should be paid to Shandong and Hebei
347 provinces due to their dominant contributions to the crop losses.

348 3. Crop loss estimations are sensitive to O₃ data sources, accumulation periods and E-R
349 functions. O₃ measurements in rural areas are in urgent need for better assessments of yield
350 losses in the future. More exposure and response experiments should also be performed for an
351 accurate quantification of crop losses.

352 4. Based on the evolution of AOT40 during the crop growing periods, timely harvest of
353 winter wheat and optimized sowing date of summer maize may be helpful for reducing the
354 O₃-induced crop losses.

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362

363 **References**

- 364 Booker, F., Muntifering, R., McGrath, M., Burkey, K., Decoteau, D., Fiscus, E., Manning, W., Krupa, S.,
365 Chappelka, A., Grantz, D., 2009. The ozone component of global change: Potential effects on
366 agricultural and horticultural plant yield, product quality and interactions with invasive species. *J. Integr.*
367 *Plant Biol.*, 51, 337-351.
- 368 Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B.,
369 Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu,
370 Y., Martin, R., Morawska, L., Pope, C.A., Shin, H., Straif, K., Shaddick, G., Thomas, M., van Dingenen,

- 371 R., van Donkelaar, A., Vos, T., Murray, C.J.L., Forouzanfar, M.H., 2017. Estimates and 25-year trends
 372 of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global
 373 Burden of Diseases Study 2015. *The Lancet*, 389, 1907-1918.
- 374 Emberson, L. D., Büker, P., Ashmore, M.R., Mills, G., Jackson, L.S., Agrawal, M., Atikuzzaman, M.D.,
 375 Cinderby, S., Engardt, M., Jamir, C., Kobayashi, K., Oanh, N.T.K., Quadir, Q.F., Wahid, A., 2009. A
 376 comparison of North American and Asian exposure–response data for ozone effects on crop yields.
 377 *Atmos. Environ.*, 43, 1945-1953.
- 378 Feng, Z., Hu, E., Wang, X., Jiang, L., Liu, X., 2015. Ground-level O₃ pollution and its impacts on food crops in
 379 China: A review. *Environ. Pollut.*, 199, 42-48.
- 380 Feng, Z., Hu, T., Tai, A.P.K., Calatayud, V., 2020. Yield and economic losses in maize caused by ambient ozone
 381 in the North China Plain (2014–2017). *Sci. Total Environ.*, 722, 137958.
- 382 Feng, Z., Kobayashi, K., Li, P., Xu, Y., Tang, H., Guo, A., Paoletti, E., Calatayud, V., 2019a. Impacts of current
 383 ozone pollution on wheat yield in China as estimated with observed ozone, meteorology and day of
 384 flowering. *Atmos. Environ.*, 217, 116945.
- 385 Feng, Z., Marco, A.D., Anav, A., Gualtieri, M., Paoletti, E., 2019b. Economic losses due to ozone impacts on
 386 human health, forest productivity and crop yield across China. *Environ. Int.*, 131, 104966.
- 387 Hu, T., Liu, S., Xu, Y., Feng, Z., Calatayud, V., 2019. Assessment of O₃-induced yield and economic losses for
 388 wheat in the North China Plain from 2014 to 2017, China. *Environ. Pollut.*, 258, 113828.
- 389 Jerrett, M., Burnett, R.T., Pope, C.A., Ito, K., Thurston, G., Krewski, D., Shi, Y., Calle, E., Thun, M., 2009.
 390 Long-term ozone exposure and mortality. *N. Engl. J. Med.*, 360, 1085-1095.
- 391 Kong, L., Tang, X., Zhu, J., Wang, Z., Li, J., Wu, H., Wu, Q., Chen, H., Zhu, L., Wang, W., Liu, B., Wang, Q.,
 392 Chen, D., Pan, Y., Song, T., Li, F., Zheng, H., Jia, G., Lu, M., Wu, L., Carmichael, G.R., 2021. A
 393 Six-year long (2013–2018) High-resolution Air Quality Reanalysis Dataset over China base on the
 394 assimilation of surface observations from CNEMC. *Earth Syst. Sci. Data*, 13, 529-570.
- 395 Li, K., Liao, H., Zhu, J., Moch, J.M., 2016. Implications of RCP emissions on future PM_{2.5} air quality and direct
 396 radiative forcing over China. *J. Geophys. Res. Atmos.*, 121, 12,985-13,008.
- 397 Lin, Y., Jiang, F., Zhao, J., Zhu, G., He, X., Ma, X., Li, S., Sabel, C.E., Wang, H., 2018. Impacts of O₃ on
 398 premature mortality and crop yield loss across China. *Atmos. Environ.*, 194, 41-47.
- 399 Lu, X., Hong, J., Zhang, L., Cooper, O.R., Schultz, M.G., Xu, X., Wang, T., Gao, M., Zhao, Y., Zhang, Y., 2018.
 400 Severe surface ozone pollution in China: A global perspective. *Environ. Sci. Technol. Lett.*, 5, 487-494.
- 401 Mills, G., Hayes, F., Simpson, D., Emberson, L., Norris, D., Harmens, H., Büker, P., 2011. Evidence of
 402 widespread effects of ozone on crops and (semi-)natural vegetation in Europe (1990–2006) in relation to
 403 AOT40- and flux-based risk maps. *Glob. Chang. Biol.*, 17, 592-613.

- 404 Monks, P. S., Archibald, A.T., Colette, A., Cooper, O., Coyle, M., Derwent, R., Fowler, D., Granier, C., Law,
405 K.S., Mills, G.E., Stevenson, D.S., Tarasova, O., Thouret, V., von Schneidemesser, E., Sommariva, R.,
406 Wild, O., Williams, M.L., 2015. Tropospheric ozone and its precursors from the urban to the global scale
407 from air quality to short-lived climate forcer. *Atmos. Chem. Phys.*, 15, 8889-8973.
- 408 Paoletti, E., De Marco, A., Racalbutto, S., 2007. Why should we calculate complex indices of ozone exposure?
409 Results from Mediterranean background sites. *Environ. Monit. Assess.*, 128, 19-30.
- 410 Peng, J., Shang, B., Xu, Y., Feng, Z., Pleijel, H., Calatayud, V., 2019. Ozone exposure- and flux-yield response
411 relationships for maize. *Environ. Pollut.*, 252, 1-7.
- 412 Pleijel, H., Broberg, M., Uddling, J., 2019. Ozone impact on wheat in Europe, Asia and North America – A
413 comparison. *Sci. Total Environ.*, 664, 908-914.
- 414 Ren, X., Shang, B., Feng, Z., Calatayud, V., 2020. Yield and economic losses of winter wheat and rice due to
415 ozone in the Yangtze River Delta during 2014–2019. *Sci. Total Environ.*, 745, 140847.
- 416 State Council of China, 1996. White Paper: the Grain Issue in China.
- 417 Schauburger, B., Rolinski, S., Schaphoff, S., Müller, C., 2019. Global historical soybean and wheat yield loss
418 estimates from ozone pollution considering water and temperature as modifying effects. *Agric. For.
419 Meteorol.*, 265, 1-15.
- 420 Seltzer, K.M., Shindell, D.T., Kasibhatla, P., Malley, C.S., 2020. Magnitude, trends, and impacts of ambient
421 long-term ozone exposure in the United States from 2000 to 2015. *Atmos. Chem. Phys.*, 20, 1757-1775.
- 422 Sinha, B., Singh Sangwan, K., Maurya, Y., Kumar, V., Sarkar, C., Chandra, B. P., and Sinha, V., 2015.
423 Assessment of crop yield losses in Punjab and Haryana using 2 years of continuous in situ ozone
424 measurements, *Atmos. Chem. Phys.*, 15, 9555–9576.
- 425 Sharma, A., Ojha, N., Pozzer, A., Beig, G., Gunthe, S.S., 2019. Revisiting the crop yield loss in India attributable
426 to ozone. *Atmos. Environ.*, X, 1, 100008.
- 427 Sun, L., Xue, L., Wang, T., Gao, J., Ding, A., Cooper, O.R., Lin, M., Xu, P., Wang, Z., Wang, X., Wen, L., Zhu,
428 Y., Chen, T., Yang, L., Wang, Y., Chen, J., Wang, W., 2016. Significant increase of summertime ozone
429 at Mount Tai in Central Eastern China. *Atmos. Chem. Phys.*, 16, 10637-10650.
- 430 Sun, L., Xue, L., Wang, Y., Li, L., Lin, J., Ni, R., Yan, Y., Chen, L., Li, J., Zhang, Q., Wang, W., 2019. Impacts of
431 meteorology and emissions on summertime surface ozone increases over central eastern China between
432 2003 and 2015. *Atmos. Chem. Phys.*, 19, 1455-1469.
- 433 Tang, H., Takigawa, M., Liu, G., Zhu, J., Kobayashi, K., 2013. A projection of ozone-induced wheat production
434 loss in China and India for the years 2000 and 2020 with exposure-based and flux-based approaches.
435 *Glob. Chang. Biol.*, 19, 2739-2752.

- 436 Tang, X., Kong, L., Zhu, J., Wang, Z., Li, J., Wu, H., Wu, Q., Chen, H., Zhu, L., Wang, W., Liu, B., Wang, Q.,
437 Chen, D., Pan, Y., Song, T., Li, F., Zheng, H., Jia, G., Lu, M., Wu, L., Carmichael, G., 2020. A Six-year
438 long High-resolution Air Quality Reanalysis Dataset over China from 2013 to 2018. V2. *Sci. Data Bank*.
- 439 Wang, T., Xue, L., Brimblecombe, P., Lam, Y., Li, L., Zhang, L., 2017. Ozone pollution in China: A review of
440 concentrations, meteorological influences, chemical precursors, and effects. *Sci. Total Environ.*, 575,
441 1582-1596.
- 442 Wang, T., Wei, X., Ding, A., Poon, C.N., Lam, K.S., Li, Y., Chan, L., Anson, M., 2009. Increasing surface ozone
443 concentrations in the background atmosphere of Southern China, 1994–2007, *Atmos. Chem. Phys.*, 9,
444 6217–6227.
- 445 Wang, X., Zhang, Q., Zheng, F., Zheng, Q., Yao, F., Chen, Z., Zhang, W., Hou, P., Feng, Z., Song, W., Feng, Z.,
446 Lu, F., 2012. Effects of elevated O₃ concentration on winter wheat and rice yields in the Yangtze River
447 Delta, China, *Environ. Pollut.*, 171, 118-125.
- 448 Xue, L., Wang, T., Louie, P. K., Luk, C. W., Blake, D. R., Xu, Z., 2014. Increasing external effects negate local
449 efforts to control ozone air pollution: a case study of Hong Kong and implications for other Chinese cities,
450 *Environ. Sci. Technol.*, 48, 10769.
- 451 Zhao, H., Zheng, Y., Zhang, Y., Li, T., 2020. Evaluating the effects of surface O₃ on three main food crops across
452 China during 2015–2018. *Environ. Pollut.*, 258, 113794.
- 453 Zhu, X., Feng, Z., Sun, T., Liu, X., Tang, H., Zhu, J., Guo, W., Kobayashi, K., 2011. Effects of elevated ozone
454 concentration on yield of four Chinese cultivars of winter wheat under fully open-air field conditions.
455 *Glob. Chang. Biol.*, 17: 2697-2706.

Table 1. Statistics of AOT40 (ppm h) during the growing period of winter wheat and summer maize from 2013 to 2018. Data (in cropland grid cells) at 1 × 1 km resolution were used for calculation.

Crop	Metrics	2013	2014	2015	2016	2017	2018
Wheat	Mean ± SD	8.5 ± 2.6	10.8 ± 3.1	11.9 ± 2.9	13.5 ± 2.3	18.0 ± 3.0	19.4 ± 3.5
	Max	15.1	19.6	19.8	18.7	25.0	28.9
	Min	1.0	2.6	3.4	6.2	6.9	6.7
Maize	Mean ± SD	13.1 ± 4.2	14.5 ± 4.3	14.8 ± 4.3	16.8 ± 3.4	22.0 ± 4.3	20.6 ± 3.9
	Max	24.1	30.1	29.2	24.0	42.1	32.4
	Min	3.1	3.7	1.8	6.2	10.2	7.1

Table 2. A summary of recent O₃-induced wheat yield loss studies in different countries. Note that the AOT40 and RYL values in the table represent the annual regional average during the crop growing period.

Study area	Study period	O ₃ data source	Growing period		E-R equation slope ^a	AOT40 (ppm h) ^b	RYL	Reference
			Length (days)	Starting date				
US	2000-2015	observation	90	N.A.	-0.0163	~12 - ~6	12.1-9.4%	Selzer et al. (2020)
India	2014-2015	regional model	90	June 15	-0.0161	N.A.	~21-26%	Sharma et al. (2019)
India	2012-2013	observation	135 or 120	Multiple dates	-0.026	10.6-17.1	27-41%	Sinha et al. (2015)
Mainland China	2015	observation	75	Apr. 1	-0.0228	N.A.	6%	Feng et al. (2019a)
Mainland China	2015-2018	observation	90	Multiple dates ^c	(-0.0205, -0.025)	8.5-14.3	20.1-33.3%	Zhao et al. (2020)
Mainland China	2014	regional model	90	Mar. 1	(-0.013, 0.0228)	N.A.	21-39%	Lin et al. (2018)
NCP of China	2015-2016	observation	75	N.A.	-0.0205	6.1-6.5	17.1-18.1%	Feng et al. (2019b)
NCP of China	2014-2017	observation	75	N.A.	-0.0205	9.6-15.1	18.5-30.8%	Hu et al. (2020)
YRD of China ^d	2014-2019	observation	75	Mar. 7, 12, or 13	-0.0205	4.6-9.4	9.4-19.3%	Ren et al. (2020)
Northern China	2013-2018	reanalysis data	75	Apr. 1	-0.0205	8.5-19.4	17.9-38.6%	This study

^a $RY = \text{slope} \times \text{AOT40} + 1$. If more than two E-R equations were used in a study, the minimum and maximum slopes are shown.

^b The Min and Max values are listed. For US, the Max values are listed first, indicating a downward trend.

^c Mar. 15 or 20 for northern China; Feb. 1, 10, or Mar. 1 for southern China.

^d The study area is the Yangtze River Delta (YRD) region of China. YRD is located on the south of NCP, and is comprised of three provinces (Jiangsu, Anhui, and Zhejiang) and one city (Shanghai).

Table 3. A summary of recent O₃-induced maize yield loss studies in different countries. Note that the AOT40 and RYL values in the table represent the annual regional average during the crop growing period.

Study area	Study period	O ₃ data source	Growing period		E-R equation slope ^a	AOT40 (ppm h) ^b	RYL	Reference
			Length (days)	Starting date				
US	2000-2015	observation	90	N.A.	-0.00356	~12 - ~3.5	3.4-1.6%	Selzer et al. (2020)
India	2011-2013	observation	90	Multiple dates	0.0067	8.4-9.4	3-5%	Sinha et al. (2015)
Mainland China	2015-2018	observation	90	June 1 or Aug. 1	-0.0036, -0.0058	10.5-13.4	5-6.3%	Zhao et al. (2020)
Mainland China	2014	regional model	90	June 1 or Aug. 1	-0.0036, -0.0067	N.A.	3-6%	Lin et al. (2018)
NCP of China	2014-2017	observation	90	N.A.	-0.00577	13.7-22.7	8.2-13.4%	Feng et al. (2020)
Northern China	2013-2018	reanalysis data	90	July. 1	-0.00577	13.1-22.0	7.5-12.8%	This study

^a $RY = \text{slope} \times \text{AOT40} + 1$. If more than two E-R equations were used in a study, the minimum and maximum slopes are shown.

^b The Min and Max values are listed. For US, the Max values are listed first, indicating a downward trend.

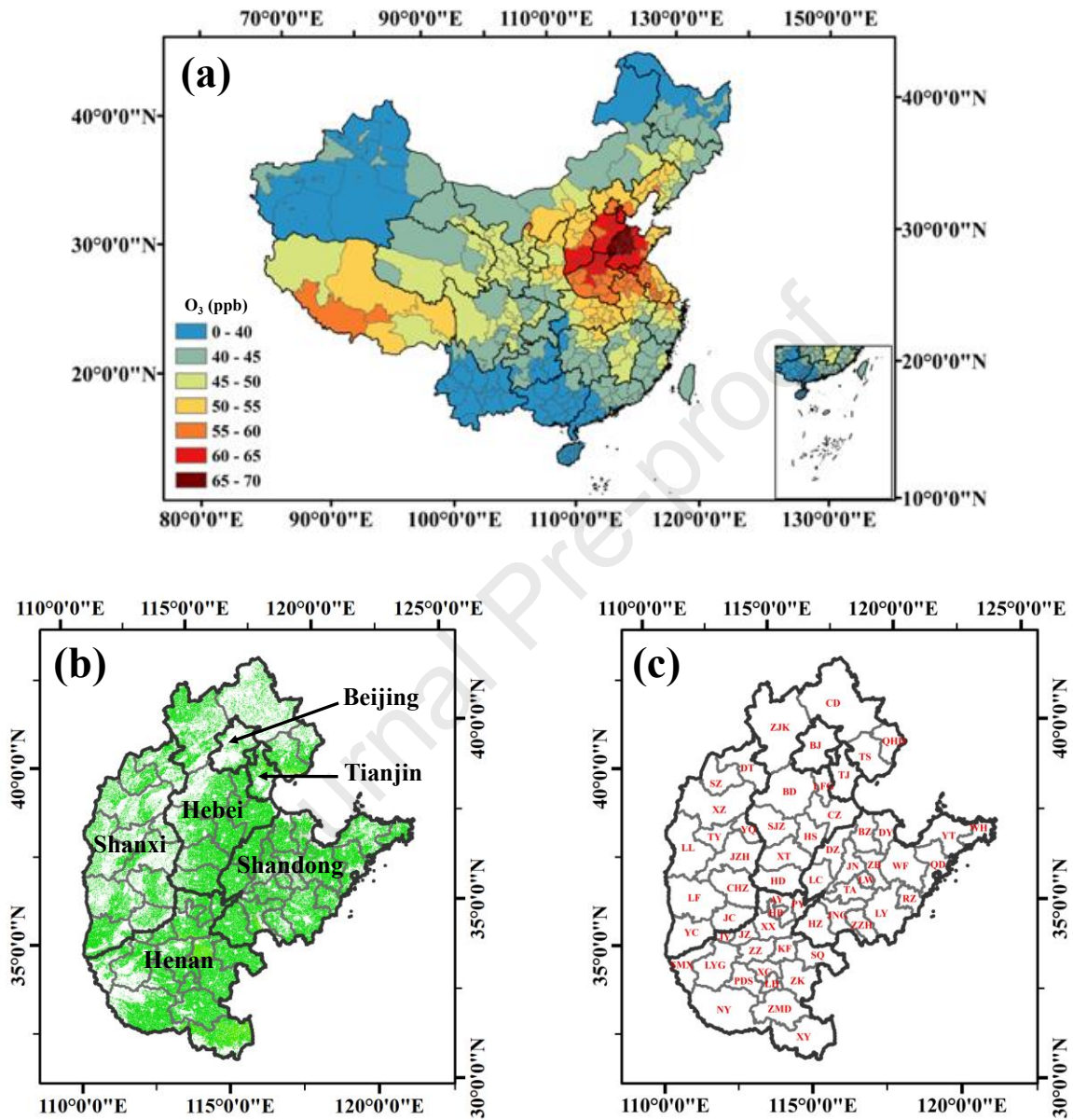


Figure 1. (a) City-level period mean daytime (08:00 – 18:00 local time, from April 1 to September 30, 2018) O₃ concentrations over China. Hourly surface O₃ concentration data used for calculation are obtained from the Chinese Air Quality Reanalysis dataset. (b) Map of the study area in this work, with green squares showing locations of the cropland. (c) City abbreviations (the full forms can be found in Table S1).

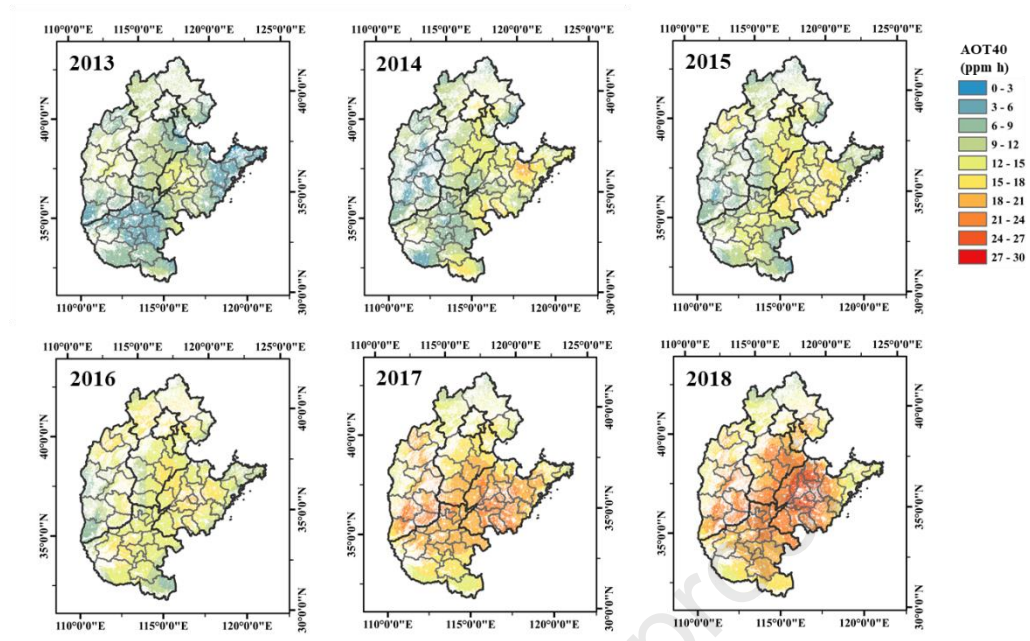


Figure 2. Spatial distributions of AOT40 over the croplands during the growing period of winter wheat from 2013 to 2018.

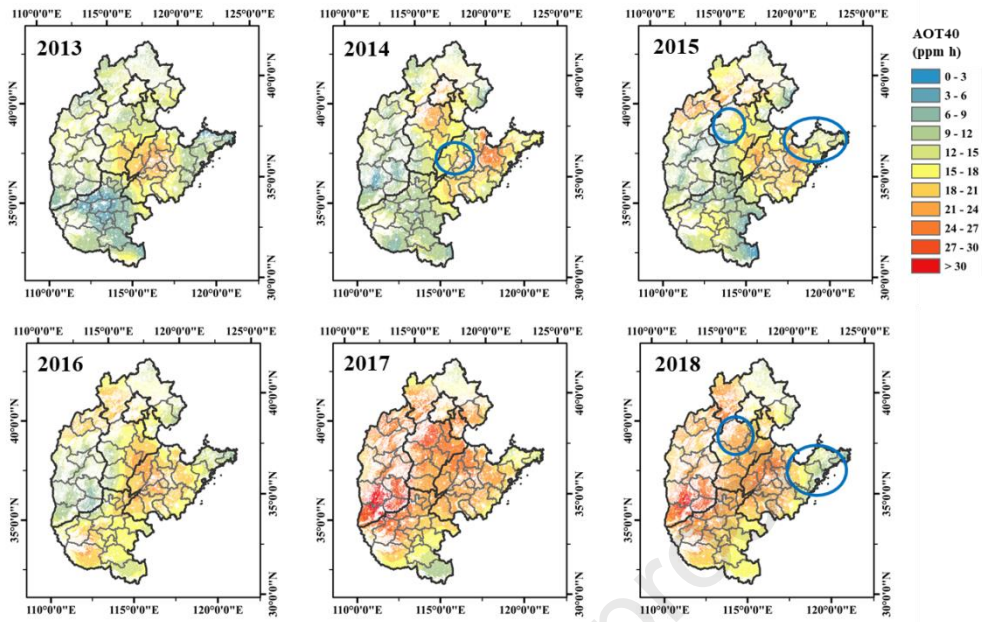


Figure 3. Spatial distributions of AOT40 over croplands during the growing period of maize (2013 – 2018). Blue circles show the areas where the AOT40 values were lower than those of the previous year.

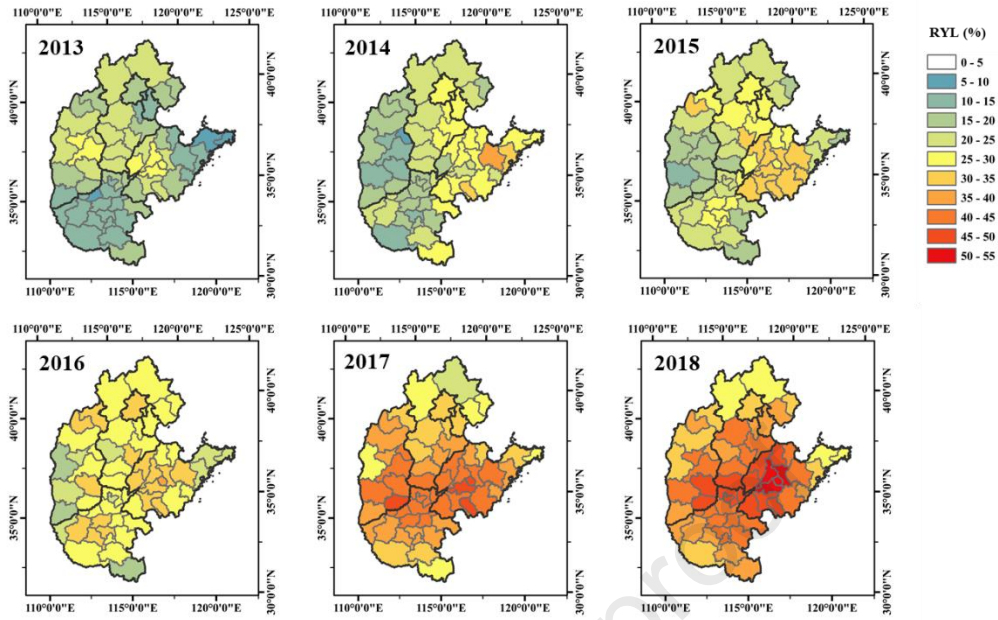


Figure 4. The estimated O_3 -induced relative yield losses of winter wheat from 2013 to 2018.

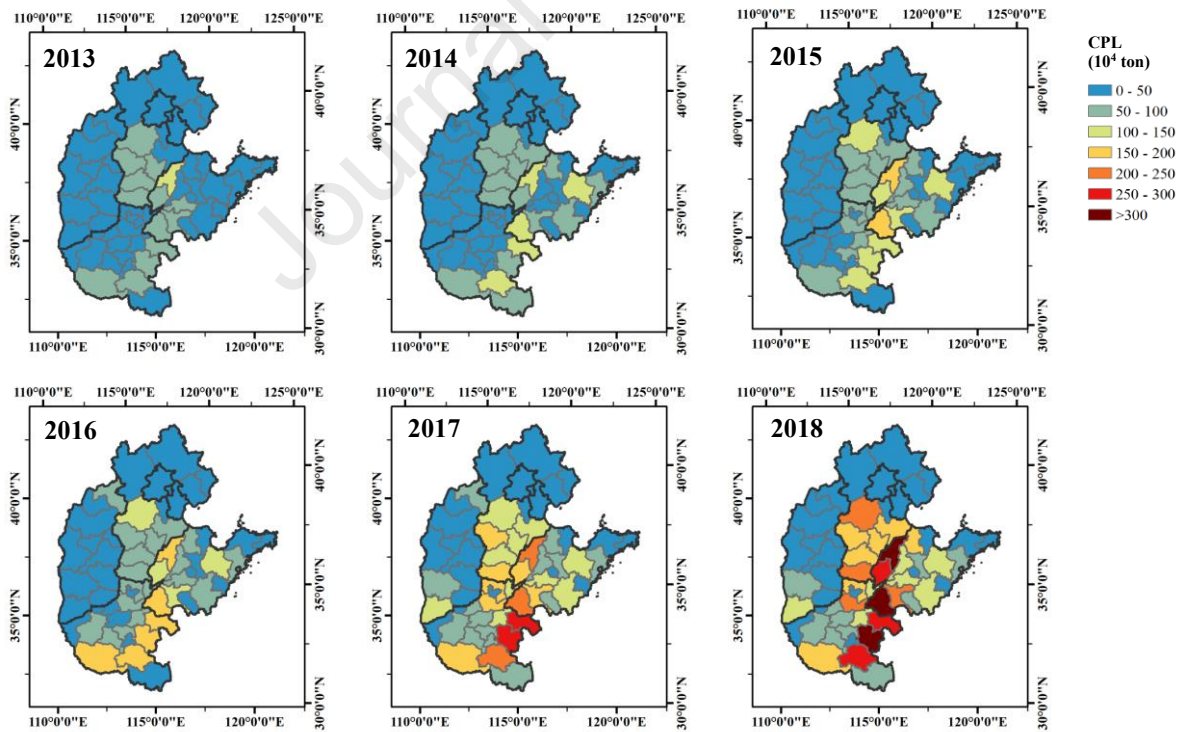


Figure 5. O_3 -induced city-level crop production losses for winter wheat from 2013 to 2018.

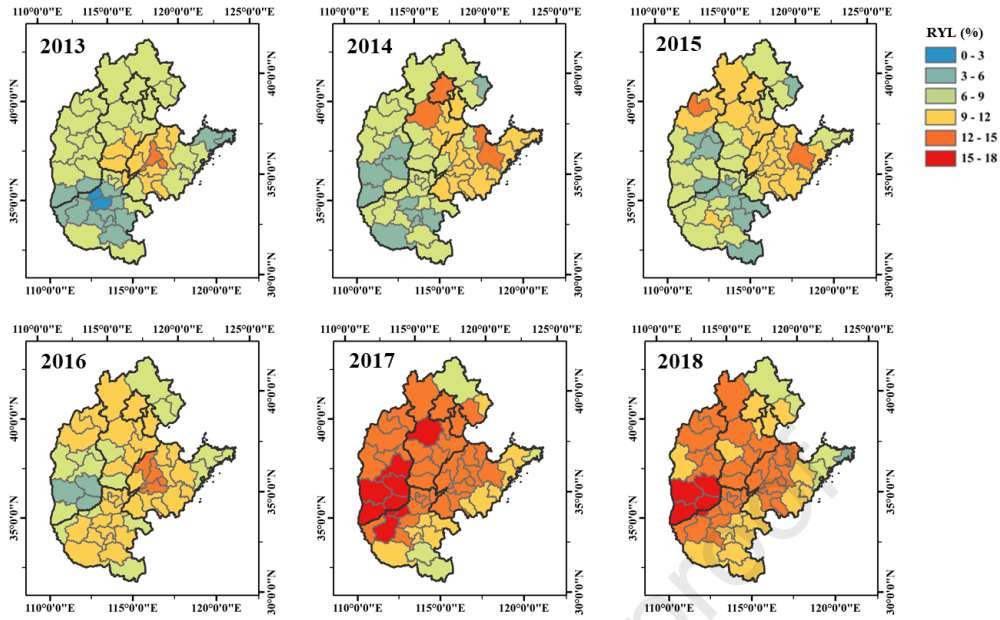


Figure 6. The estimated O_3 -induced relative yield losses of summer maize from 2013 to 2018.

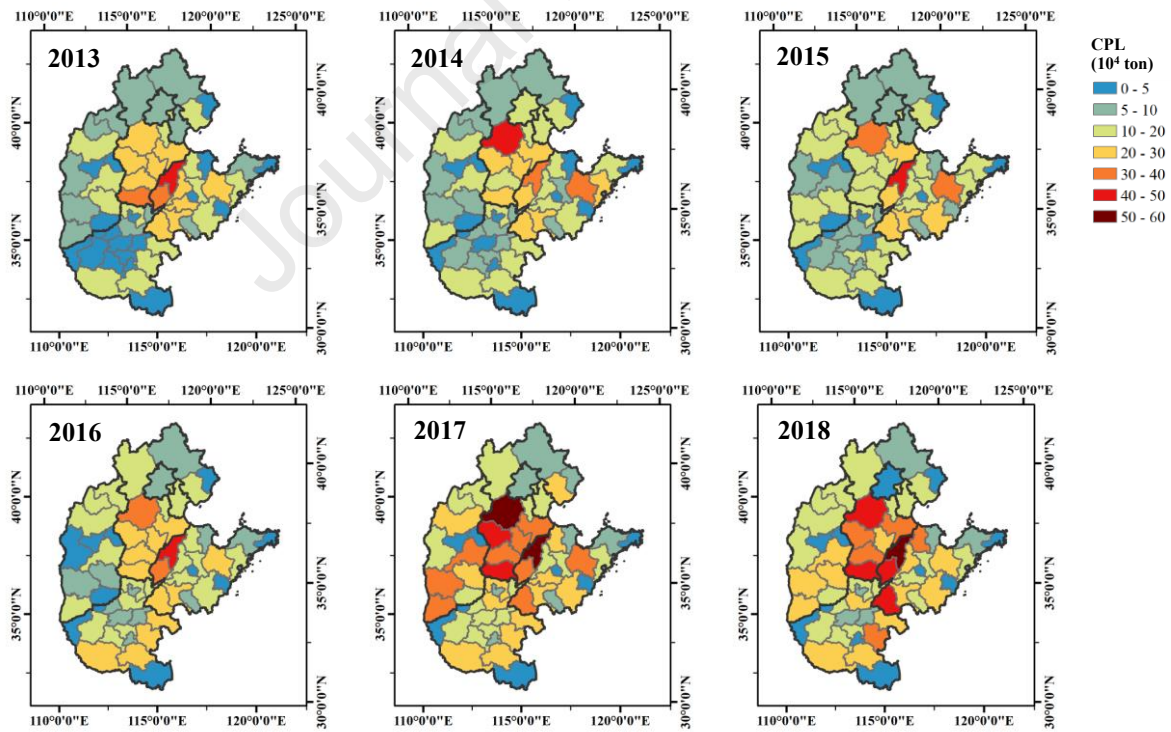


Figure 7. O_3 -induced city-level crop production losses for summer maize from 2013 to 2018.

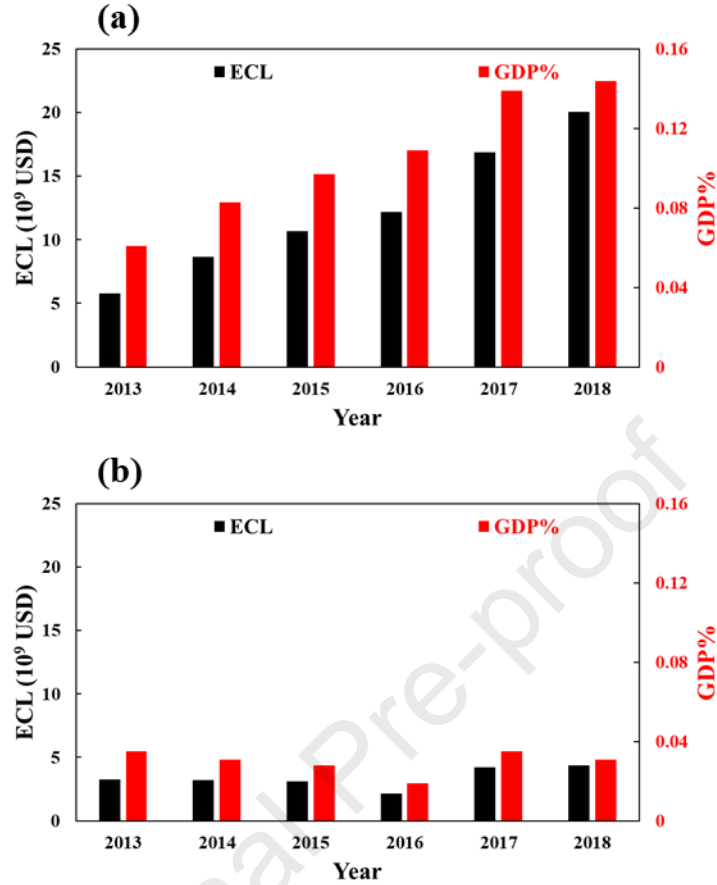


Figure 8. The estimated O₃-induced total economic cost losses of (a) winter wheat and (b) summer maize and losses as a percent of China GDP from 2013 to 2018.

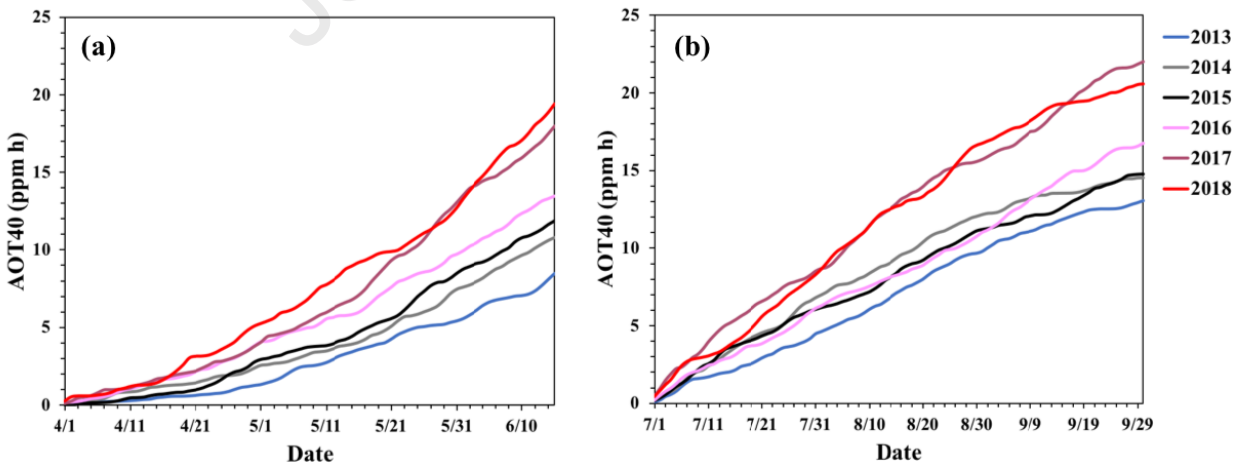


Figure 9. Evolution of the regional mean AOT40 during the growing period of (a) winter wheat and (b) summer maize from 2013 to 2018.

Crop yield losses were estimated using high resolution air quality reanalysis data and land use data.

Crop losses in northern China increased with time.

Hot spots of crop losses in northern China were determined.

Journal Pre-proof

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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