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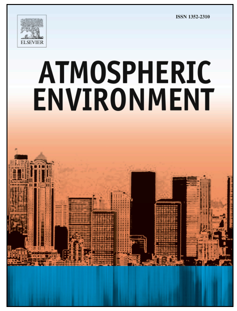

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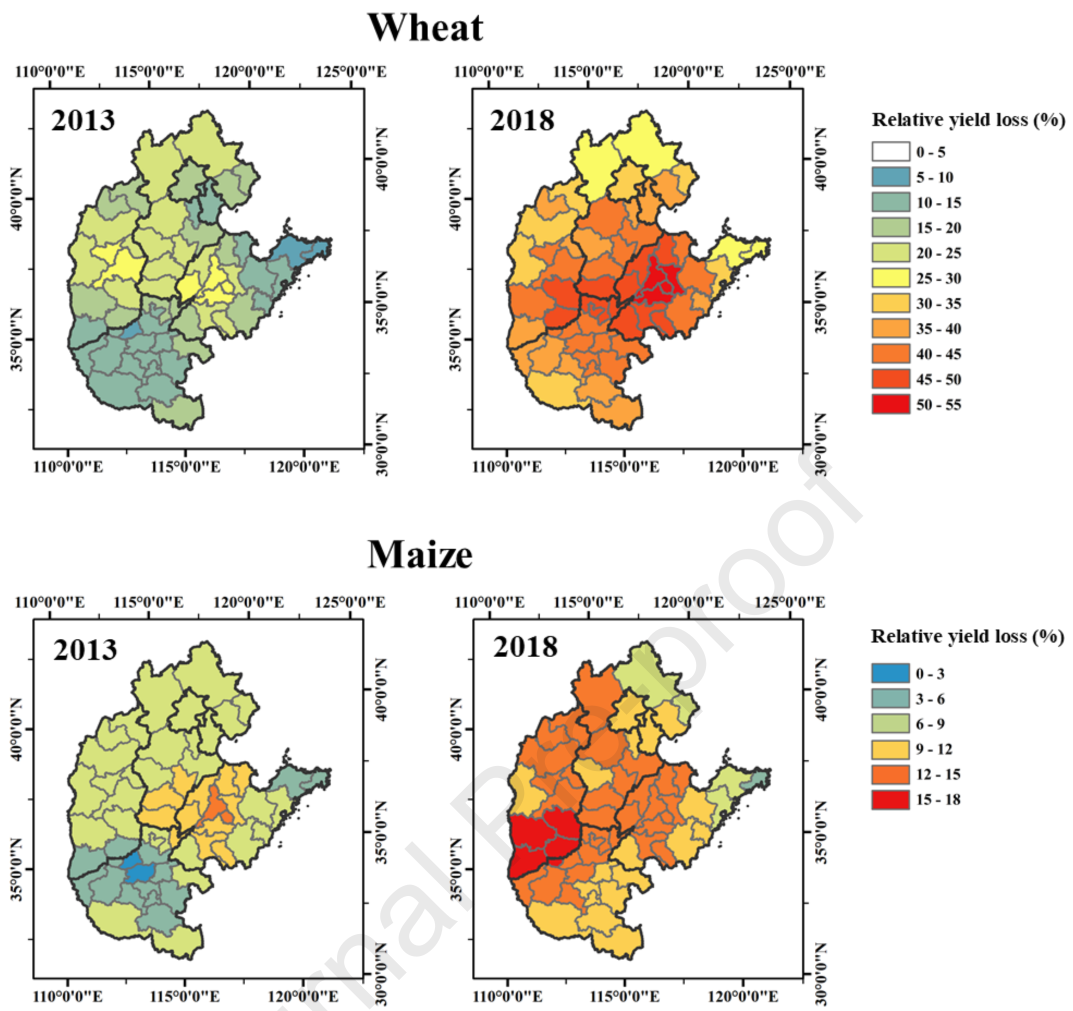
Wheat
2013
2018
Relative yield loss (%)
0 - 5
5 - 10
10 - 15
15 - 20
20 - 25
25 - 30
30 - 35
35 - 40
40 - 45
45 - 50
50 - 55
Maize
2013
2018
Relative yield loss (%)
0 - 3
3 - 6
6 - 9
9 - 12
12 - 15
15 - 18
110°0'0"E
115°0'0"E
120°0'0"E
125°0'0"E
30°0'0"N
35°0'0"N
40°0'0"N

Assessment of O_3-induced crop yield losses in northern China during 2013-2018 using high-resolution air quality reanalysis data

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Abstract

Long-term exposure of food crops to high concentrations of ambient ozone (O_3) can cause significant yield reductions. O_3-induced crop loss studies are limited in China, especially in the North China Plain (NCP) where agricultural resources are abundant and O_3 concentrations are high. In this study, we quantify the O_3-induced adverse impacts on wheat and maize over the NCP and Shanxi province during 2013-2018 through the use of high-resolution air quality reanalysis dataset and land-use dataset. Results show that the accumulated hourly O_3 concentration above 40 ppb (AOT40) in croplands experienced an upward trend, with an annual increase of 2.2 ppm h (18.1%) during the wheat growing period and 1.5 ppm h (10.9%) during the maize growing period from 2013 to 2018. O_3-induced relative yield losses grew from 17.9% in 2013 to 38.6% in 2018 for wheat, and ranged from 7.5-11.9% for maize. The estimated crop production losses also increased over time. Shandong and Hebei provinces are the hot spots of crop losses and priorities should be given to them for O_3 pollution prevention. Comparison with previous studies shows that uncertainties still exist in crop loss estimations. More rural O_3 measurements and localized crop exposure-response experiments should be performed for better assessments.

Keywords: crop yield losses, ozone, North China Plain

1. Introduction

China has nearly 20% of the world's population, but less than 10% of its arable land. Due to rapid economic/population growth, rising living standards and land scarcity, China has become the world's largest agricultural importer (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 has a long-standing grain self-sufficiency policy, i.e. satisfying a minimum of 95% of national demand of major staple crops (rice, wheat and maize) through domestic production (State Council of China, 1996). In 2019, China produced 17.4% of the world's wheat and 22.7% of the world's maize (data retrieved from http://www.fao.org/faostat/en/#data/QC, access date 5 December 2020). With China's limited agricultural land resources, achieving greater yields on existing croplands is thus essential to preserve self-reliance with the growing food demand.

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

Using experimentally derived exposure-response (ER) functions, numerous studies have been performed to assess the crop yield losses at the global or regional scale. A recent study by Schauberger et al. (2019) examined the global historical (between 2008 and 2010) soybean and wheat relative yield losses (RYL) from O_3 pollution with consideration of the modifying effects of water and temperature. They reported that global soybean losses varied between 2% and 10% for different countries; European/North American wheat losses varied between 0% and 27%; Asian wheat losses ranged from 4% to 39%. Using different methods, Seltzer et al. (2020) assessed the long-term impacts of O_3 on agriculture over continental US and found improvements of crop (maize, soybeans and wheat) yields, with RYL values dropping from 3.4% (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% in 2015, respectively. Sharma et al. (2019) estimated that O_3 led to 21% RYL for wheat and 6% RYL for rice in year 2014-2015 in India. Tang et al. (2013) estimated that in the year 2000, the RYL of wheat caused by O_3 in China and India were 6.4–14.9% and 8.2–22.3%, respectively. Overall, estimation of losses from these studies indicates that impacts of O_3 exposure on crop yields are higher in Asia than in US and Europe.

In the context of the growing food demands and worsening ozone pollution in China, the demand for quantifying ozone-associated RYL increases. A few studies specifically estimated O_3-attributed crop yield reductions in China but presented quite different results. For example, RYL of wheat induced by O_3 in 2015 were estimated to be as low as 6% to as high as 33.3% (Feng et al., 2019a; Feng et al., 2020; Hu et al., 2020). The large uncertainties are mainly introduced by the estimate of O_3 exposure and the choice of the E-R function. First, O_3 exposure estimation can rely on observational or model-simulated data. There are pros and cons of each method. While measurements reflect the real concentration of air pollutants at the monitoring site, they have a limited coverage of space and time, masking the spatiotemporal variability of O_3. One relevant issue is that if most of the air quality monitoring stations are located in cities, measured data may not be representative of the pollution level in the rural areas where the crops are planted. As an alternate data source for the O_3 exposure calculation, air quality modeling data are not limited by time or space, but suffer uncertainties from the spatial resolution, meteorology, emission inventory, chemical mechanisms, etc. Second, E-R functions derived for a certain food crop can differ significantly under influences of different climate types and crop genotypes. For example, Schauberger et al. (2019) reported that Asian crops are more vulnerable to O_3 pollution compared to crops in US or Europe. Such differences influence the assessment and may lead to great discrepancies in the crop loss estimates.

In this study, we aim to determine more accurately the threat of O_3 pollution on crops by using a high spatial resolution (15 × 15 km) air quality reanalysis dataset that optimally combines the observations with air quality forecasts through data assimilation, a high resolution (1 × 1 km) land use dataset (for identifying locations of croplands), E-R functions derived for crops grown in China, and city-level crop yields data. The study area of this work, where agriculture is a major source of livelihood for rural communities (Fig. S1), covers the North China Plain (NCP) region (i.e., Beijing, Tianjin, Hebei province, Henan province, and Shandong province), and Shanxi province. Figure 1 shows ozone concentrations are high in this area during the warm seasons. According to the Statistical Yearbook of China (http://www.stats.gov.cn/tjsj/ndsj/, last access: 5 December 2020), in 2019, this area produced 8.05×10^7 ton wheat and 7.85×10^7 ton maize, accounting for 60.2% and 30.1% of the national total production, respectively. Consequently, a better understanding of O_3-induced crop losses in this area is of great significance. This work assesses the O_3-related yield and economic losses from a relatively long-term perspective (2013-2018) and results from this study improve over previous studies by incorporating locally derived E-R relationships of crops with air pollutant data that are superior (by using reanalysis data and considering the variations of O_3 concentrations in crop growing areas at a fine scale) to both measurements and model simulations.

2. Methodology

2.1 Data sources

Hourly surface O_3 concentration data over the study area spanning 2013-2018 were obtained from the Chinese Air Quality Reanalysis dataset (CAQRA) (Tang et al., 2020). This dataset was produced by the chemical data assimilation system (ChemDAS, developed by the Institute of Atmospheric Physics, Chinese Academy of Sciences) which assimilates surface air quality observations from China National Environmental Monitoring Center based on the ensemble Kalman filter (the assimilation algorithm) and the Nested Air Quality Prediction Modeling system (a three dimensional chemical transport model). Surface concentrations of six air pollutants ($PM_{2.5}$, PM_{10}, NO_2, SO_2, CO and O_3) are provided at high spatial (15×15 km) and temporal (1 hour) resolutions. Comparisons with observations from over 1000 air quality monitoring stations and the Copernicus Atmosphere Monitoring Service reanalysis dataset (produced by the European Centre for Medium-Range Weather Forecasts) show that CAQRA has excellent performance in reproducing the spatiotemporal variations of surface concentrations of air pollutants. Detailed descriptions of this dataset can be found in Kong et al. (2021).

The land use data (1×1 km resolution) for 2015 were downloaded from the Resource and Environment Science and Data Center (http://www.resdc.cn/, last access: 5 December 2020). According to the Statistical Yearbook of China (http://www.stats.gov.cn/tjsj/ndsj/, last access: 5 December 2020), the total area of the cropland in China was 240, 000 km^2 in 2013 and 236, 000 km^2 in 2018. Thus we assume locations of the cropland grid cells in the land use dataset remain unchanged during 2013-2018 and crops (wheat and maize) are cultivated in those grid cells.

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

2.2 AOT40 calculation

We use the AOT40 (accumulated hourly O_3 concentration above 40 ppb, Eq. 1), an exposure index that is widely used by the ozone research community, for the assessment of the potential risk of ambient O_3, for estimations of yield losses of winter wheat and summer maize (Paoletti et al. 2007). The accumulation periods for wheat and maize are defined as April 1 to June 15 (springtime) and July 1 to September 30 (summertime), respectively.

$$\mathrm{AOT40(ppm\ h)} = \sum_{i=1}^{n} ([O_3]_i - 40)\,/1000, \text{for } O_3 \geq 40 \text{ ppb} \qquad \text{Eq. 1}$$

Where, $[O_3]_i$ is the hourly O_3 concentration in ppb during the daytime hours (between 8:00 and 18:00 of China Standard Time); n is the number of hours over the crop growing season.

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

2.3 Crop relative yield and economic loss estimation

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

For wheat:

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

For maize:

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

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

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

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

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

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

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

3. Results and Discussion

3.1 Magnitudes of AOT40

3.1.1 AOT40 during the growing period of wheat

Table 1 summarizes the regional mean, maximum and minimum values of springtime AOT40 for each year. The average AOT40 over the study area had increased from 8.5 ppm h in 2013 to 19.4 ppm h in 2018, with an annual increase of 2.2 ppm h (18.1% growth per year). Moreover, O_3 exposure increased drastically (by 33.3%) from 2016 to 2017. This upward trend of O_3 exposure is in general consistent with the worsening O_3 pollution in the NCP region (Sun et al., 2016), and demonstrates the growing risks for winter wheat.

Figure 2 shows the gridded spatial distributions of AOT40 over the croplands during the growing period of wheat for each year. It is apparent that springtime AOT40 featured significant increases throughout the study period. In 2013, values of AOT40 in most of the cropland grid cells were below 15 ppm h. In comparison, in 2017 and 2018, AOT40 in more than half of the croplands were greater than 15 ppm h. On an annual basis, higher levels of AOT40 were distributed in the intensively farmed areas (i.e., the central part of the study area). Specifically, for all years, cities in the west of Shandong province and southeast of Hebei province suffered from relatively high AOT40, indicating elevated risks for wheat grown in those regions. Substantial increases of AOT40 also occurred over the northern part of Henan province from 2016 to 2018, and the widespread O_3 pollution would put more vegetation under greater risks.

3.1.2 AOT40 during the growing period of maize

The regional mean, maximum and minimum values of summertime AOT40 from 2013 to 2018 can be found in Table 1. In general, similar to that of springtime AOT40, summertime O_3 exposure also exhibited an upward trend. The average values of AOT40 over the study area during the maize growing period ranged from 13.1 ppm h to 22.0 ppm h, with an increase rate of 1.5 ppm h (10.9%) per year from 2013 to 2018. It should also be noted that summertime AOT40 peaked and experienced the fastest rate of increase in 2017, which was a 31.0% increase compared to the average value in 2016 (16.8 ppm h). Meanwhile, O_3 exposure decreased by 6.3% from 2017 (22.0 ppm h) to 2018 (20.6 ppm h). If 2018 had been excluded, the average increase of regional mean AOT40 (2013 - 2017) per year would be 2.2 ppm h, which was the same as that of the springtime AOT40. While the estimated O_3 exposure was higher in the summertime (Table 1, Figs. 2 and 3), the percentage increase rate of AOT40 during the growing period of wheat was faster than that during the growing period of maize. Considering the fact that wheat is less O_3-tolerant than maize in chamber/field studies (Zhu et al., 2011; Peng et al., 2019), yield reductions of winter wheat are expected to be higher than those of summer maize. This will be discussed in Section 3.2.

Figure 3 presents the gridded spatial distributions of AOT40 over the croplands during the growing period of maize for each year. Though summertime AOT40 experienced an overall increase from 2013 to 2018, the changes were somewhat inhomogeneous. Being the hot spots of O_3 pollution, AOT40 in certain areas of Shandong and Hebei provinces did not show consistent increases over time. The 2014, 2015 and 2018 AOT40 in some regions were lower than values in 2013, 2014 and 2017, respectively (see blue circles in Fig. 3). The substantial variations of AOT40 indicate the necessity of the use of high-resolution O_3 data for crop loss estimation. Figure 3 also shows that prior to 2016, most parts of Shanxi and Henan provinces had relatively low O_3 exposure (< 15 ppm h). In contrast, for 2017 and 2018, the majority of AOT40 exceeded 20 ppm h, and some extremely high values occurred near the borders of Shanxi and Henan provinces. Such widespread increase of O_3 exposure would affect more crops and lead to more yield reductions.

3.2 Estimation of crop yield and economic losses

Because the relative yield losses and AOT40 are linearly related (see Equations 2-4), their spatial and temporal distributions are expected to be similar. Meanwhile, crop production losses are dependent upon both relative yield losses and crop production; economic cost losses are functions of both crop production losses and the purchase price. In the following section, the O_3-associated yield and economic cost losses for winter wheat and summer maize will be discussed separately.

3.2.1 Yield and economic cost losses of winter wheat

As shown in Figure 4, the city-specific RYL of wheat due to O_3 exposure increased substantially over the study period. The spatial averages of RYL over the study area were 17.9%, 21.4%, 23.6%, 27.6%, 35.9% and 38.6% for 2013, 2014, 2015, 2016, 2017 and 2018, respectively. The regional highest RYL (2013: 28.2% in Laiwu; 2014: 35.3% in Weifang; 2015: 33.8% in Linyi; 2016: 37.1% in Laiwu; 2017: 47.1% in Jincheng of Shanxi province, but 46.1% in Tai'an; 2018: 52.2% in Ji'nan) kept occurring in cities of Shandong province. The widespread and intense impacts of O_3 pollution on winter wheat were most apparent in 2017 and 2018, with most cities (84.7% in 2017 and 89.8% in 2018) suffering more than 32% of yield losses. In 2018, the estimated RYL in cities in the west of Shandong (i.e., Binzhou, Dezhou, Zibo, Ji'nan, Tai'an, Laiwu, Liaocheng and Ji'ning) were close to 50%, indicating serious threats for wheat from O_3 pollution. The lowest value of annual RYL for wheat also increased over time, and these estimated minimum values occurred in cities near the boundaries of the study area (i.e., 8.8% in Weihai and Yantai in 2013, 9.2% in Yangquan in 2014, 13.2% in Linfen in 2015, 16.5% in Yuncheng in 2016, 24.3% in Chengde in 2017 and 26.1% in Zhangjiakou in 2018).

City-level production losses of winter wheat are presented in Figure 5. Cities with high CPL were mostly located in the main wheat production region (Shandong, Henan and Hebei provinces). CPL increased drastically over time. Estimated total CPL in 2013, 2014, 2015, 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 5885.7×10^4 tons, respectively, amounting to 13.2%, 17.9%, 20.6%, 23.7%, 37.7% and 44.8% of the national wheat production of the respective year. It should be emphasized that this area is the major wheat production region in China, which contributes to the majority (e.g., 60.2% in 2019) of national wheat production. Calculated annual total ECL (based on Eq. 6 and Table S2) and losses as a percent of China gross domestic product (GDP, obtained from the Statistical Yearbook) are shown in Figure 8(a). O_3-related economic losses increased remarkably during the study period. The ECL of wheat in 2018 was 20.1 billion USD or 132.7 billion CNY (representing 0.144% of 2018 GDP), which was 3.7 times of the economic loss in 2013.

3.2.2 Yield and economic cost losses of summer maize

The city-level relative yield losses of maize due to O_3 exposure are shown in Figure 6. The spatial averages of RYL over the study area were 7.5%, 8.3%, 8.5%, 9.4%, 12.8% and 11.9% for 2013, 2014, 2015, 2016, 2017 and 2018, respectively. These values were much lower than the estimated mean RYL for wheat, reflecting that maize was less affected by O_3 pollution. Like the summertime AOT40, RYL of maize were greatest in 2017 (the estimated RYL in 44 out of 59 cities exceeded 12%). The largest RYL of maize occurred in Shandong province in 2013 (12.9% in Laiwu), 2014 (13.8% in Weifang) and 2016 (12.4% in Dezhou), but in Shanxi province in other years (12.8% in Shuozhou in 2015, 17.3% in Jincheng in 2017, and 16.3% in Jincheng in 2018). Meanwhile, the estimated lowest RYL value for each year occurred in cities of different provinces (i.e., 2.3% in Jiaozuo in 2013, 4.1% in Linfen in 2014, 4.3% in Yangquan in 2015, 4.7% in Jincheng in 2016, 6.6% in Xinyang in 2017, 5.2% in Weihai in 2018). Variations of the temporal distributions of RYL in spring and summer indicate the seasonal differences of O_3 pollution characteristics.

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

3.3 Comparison of RYL with other studies and recommendations

Estimated crop losses may differ as a result of differences in estimated O_3 exposure, use of different E-R equations, as well as different estimation units (county-level, province-level, city-level, etc.). To place our results in a broader context, Table 2 and 3 summarize the results from recent studies that focus on assessments of O_3-induced crop losses on the regional scale. It is apparent that except for Feng et al. (2019a), the estimated RYL of wheat/maize for recent years by other Chinese and Indian studies are significantly higher than those in US. Being the top two most populous countries in the world, reducing O_3 pollution would not only increase the crop yields, but also decrease related health risks.

The estimated AOT40 and RYL from this work are in general within the range of values reported by other Chinese studies. Calculated annual increase rates of AOT40 during the wheat growing period in this study, Zhao et al. (2020) and Hu et al. (2020) are quite close, with the respective values of 2.2, 2.1, and 2.0 ppm h yr^{-1}, though variations of same year AOT40 are large. AOT40 estimations are dependent on both O_3 data source and the assumed crop growth period. Higher daytime O_3 concentrations and longer accumulation periods would lead to an increase in AOT40 and thus higher RYL using the same E-R equation. Taking the year 2015 for example, the reported lowest RYL for wheat was 6% in Feng et al. (2019a), and the highest value was 22.7% in Hu et al. (2020). As the two studies both used observations as the O_3 data source, the RYL discrepancy may be caused by the accumulation period differences. The other reason might be that the former study focused on the national RYL, while the latter focused on the NCP area where O_3 levels were high. This point of view is supported by Zhao et al. (2020), who reported 33.3% national RYL in 2018, but much higher RYL in polluted areas (Hebei: 55.3%, Shandong: 48%, Henan: 50.9%, Shanxi: 49.9%).

Table 2-3 show definitions of crop growing seasons in different studies vary significantly. To investigate the influences of the accumulation period, we calculated AOT40 based on different accumulation periods and results for RYL are listed in (Table S3). For wheat, an earlier start time of the growing period results in lower levels of O_3 exposure. This is expected because O_3 concentrations are lower in March than in the warmer months. Assuming the start date to be March 10, RYL of 2018 wheat was estimated to be 26.9%, which is significantly lower than 38.6% (RYL assuming the start date to be April 1). For maize, an earlier start time of the growing period leads to higher estimated levels of O_3 exposure. Assuming the start date to be June 1, RYL of 2018 wheat was estimated to be 16.7%, which is higher than 12.8% (RYL assuming the start date to be July 1). Variations of RYL for maize associated with changes of the growing period are smaller than those for wheat, due to the crop-sensitivity differences to O_3 exposure. Our results indicate the start, end dates and duration of the crop growth periods can impact RYL estimations significantly and highlight the importance of crop phenology data for better assessments.

The estimated losses can differ significantly due to the selection of E-R functions as well. Results from Lin et al. (2018) indicate that by adopting different E-R equations, the calculated RYL for both wheat and maize varied by almost a factor of 2. This emphasizes the need to derive localized O_3 exposure and crop yield relationships that are suitable for use in specific climates of China.

It is not straight forward to compare results from this work with Hu et al. (2020) and Feng et al. (2020), because of differences in O_3 data source and the assumed crop growth period, both of which can affect RYL remarkably. Though results differ, all studies found rising levels of O_3 exposure and decreases in crop yields. In future, more O_3 measurements in the rural areas are required to improve the future estimates of crop losses, in view of the fact that the existing air quality monitoring network is mainly established in urban areas in China.

Despite the high uncertainties in existing estimations of O_3-induced crop losses, we provide recommendations for reducing O_3 adverse impacts on the basis of the evolution of AOT40 during the crop growing seasons. As shown in Figure 9(a), AOT40 rose faster in the late growing period of winter wheat. In 2017 and 2018, accumulated O_3 exposure in the last 7 days (from to June 9 to June 15) were 2.67 and 2.80 ppm h, respectively, leading to more than 5% estimated relative yield losses. This indicates at current O_3 levels, the timely harvest of wheat can help reduce O_3 exposure and minimize the losses. Figure 9(b) shows AOT40 increased steadily during the maize growing period, but with a slower rate in late September. Thus, optimizing the sowing date of maize towards sowing at a later time, may help increase crop yields. Nevertheless, it is important to remember that our suggestions are made to reduce the O_3-related crop losses by avoiding high O_3 days. The time of sowing and harvesting is typically determined by local meteorological conditions (such as sunlight, temperature, and precipitation), and changing this time window might not be realistic and would probably also induce yield losses. In the long term, O_3 pollution mitigation is the most meaningful way to minimize crop losses.

4 Conclusions

In this study, we estimated the relatively long-term (2013-2018) city-level threat of O_3 air pollution on winter wheat and summer maize in the North China Plain by using an air quality reanalysis data set that are superior to both measured and model simulated O_3 data (method used by previous studies), a high resolution land use data set (not considered by previous studies), and E-R functions derived for crops in China. The main conclusions are as follows.

1. The O_3 exposure (AOT40) showed a significant upward trend from 2013 to 2018 in the study area, with an annual increase of 2.2 ppm h (18.1%) during the wheat growing period (springtime) and 1.5 ppm h (10.9%) during the maize growing period (summertime). In general, AOT40 exhibited an upward trend in both seasons, and increased faster in spring.

2. The O_3-induced relative yield losses increased from 17.9% in 2013 to 38.6% in 2018 for winter wheat, and ranged from 7.5-11.9% for summer maize. The estimated crop production losses also increased with time. Special attention should be paid to Shandong and Hebei provinces due to their dominant contributions to the crop losses.

3. Crop loss estimations are sensitive to O_3 data sources, accumulation periods and E-R functions. O_3 measurements in rural areas are in urgent need for better assessments of yield losses in the future. More exposure and response experiments should also be performed for an accurate quantification of crop losses.

4. Based on the evolution of AOT40 during the crop growing periods, timely harvest of winter wheat and optimized sowing date of summer maize may be helpful for reducing the O_3-induced crop losses.

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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 O_3-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] $\mathrm{RY} = \mathrm{slope} \times \mathrm{AOT40} + 1$. 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 O_3-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] $\mathrm{RY} = \mathrm{slope} \times \mathrm{AOT40} + 1$. 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.

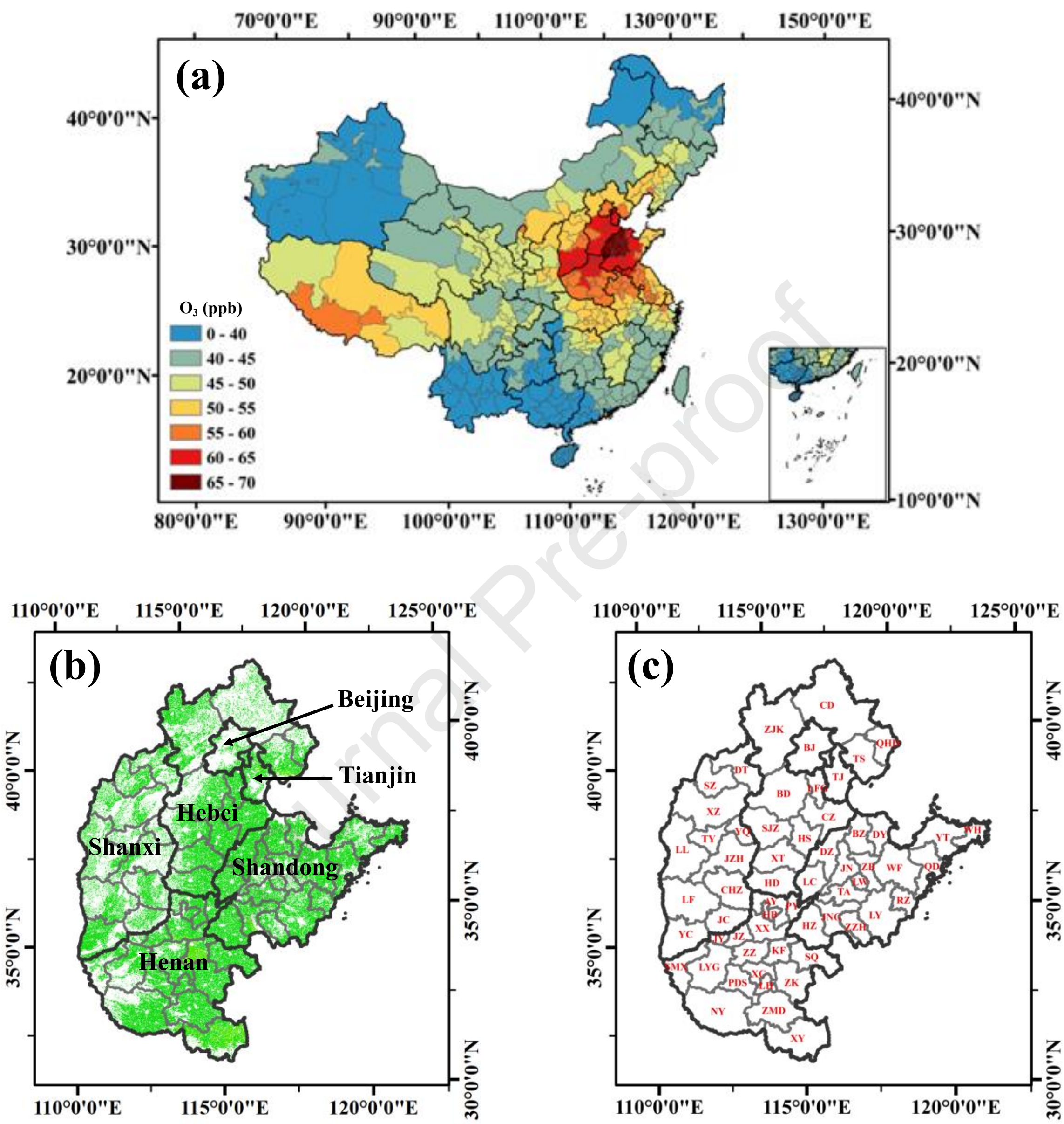

Figure 1. (a) City-level period mean daytime (08:00 – 18:00 local time, from April 1 to September 30, 2018) O_3 concentrations over China. Hourly surface O_3 concentration data used for calculation are obtained from the Chinese Air Quality Reanalysis dataset. (b) Map of the study area in this work, with green squares showing locations of the cropland. (c) City abbreviations (the full forms can be found in Table S1).

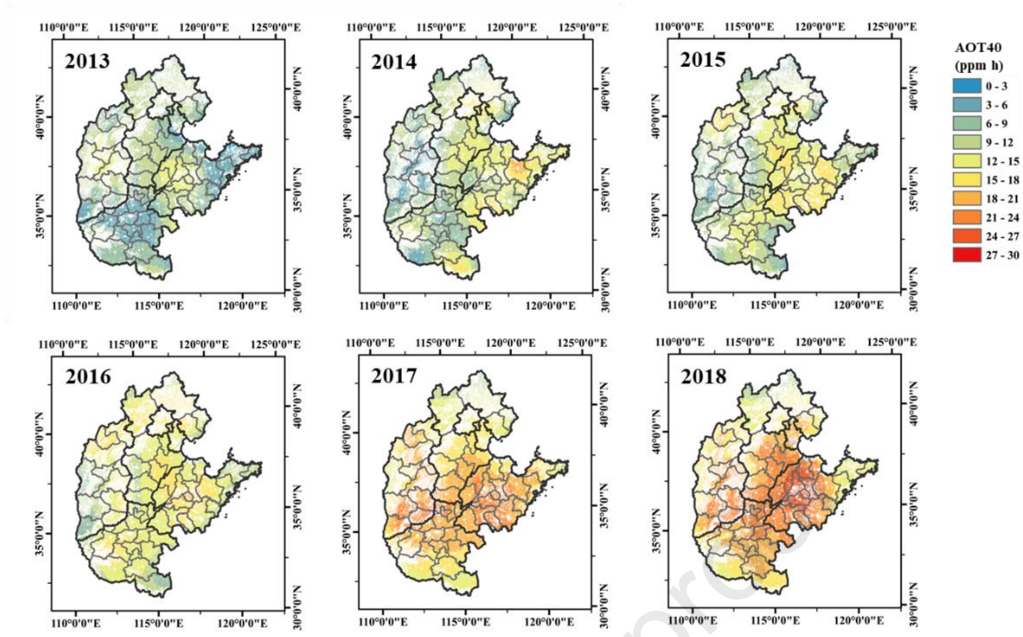

Figure 2. Spatial distributions of AOT40 over the croplands during the growing period of winter wheat from 2013 to 2018.

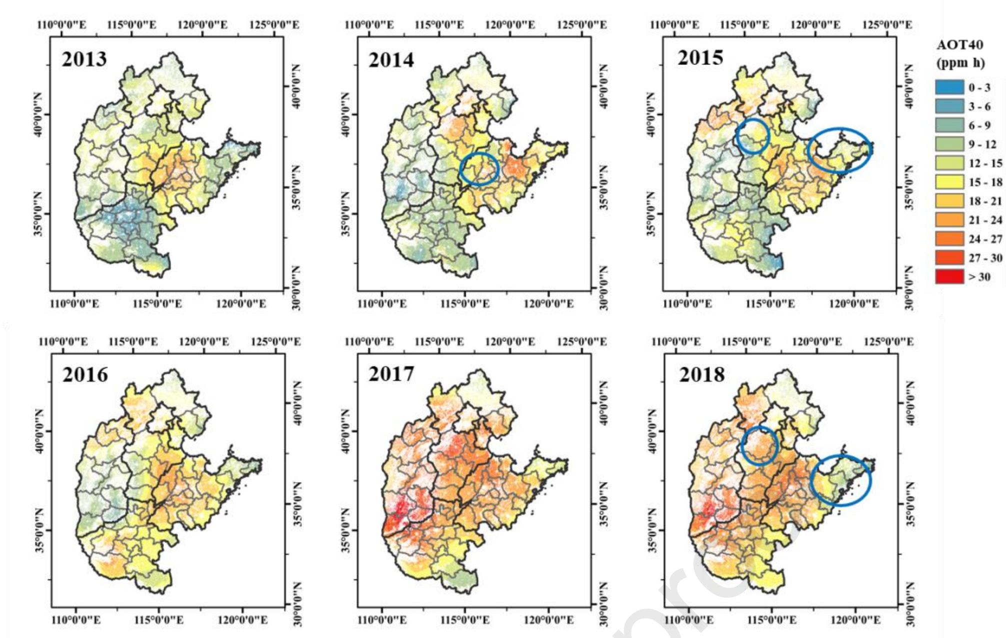

Figure 3. Spatial distributions of AOT40 over croplands during the growing period of maize (2013 – 2018). Blue circles show the areas where the AOT40 values were lower than those of the previous year.

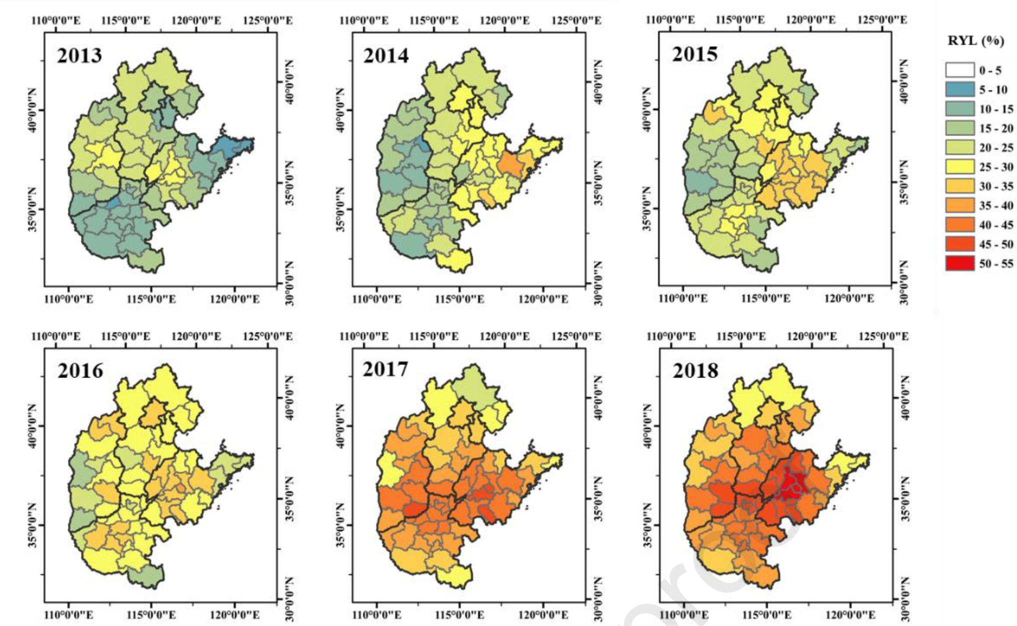

Figure 4. The estimated O_3-induced relative yield losses of winter wheat from 2013 to 2018.

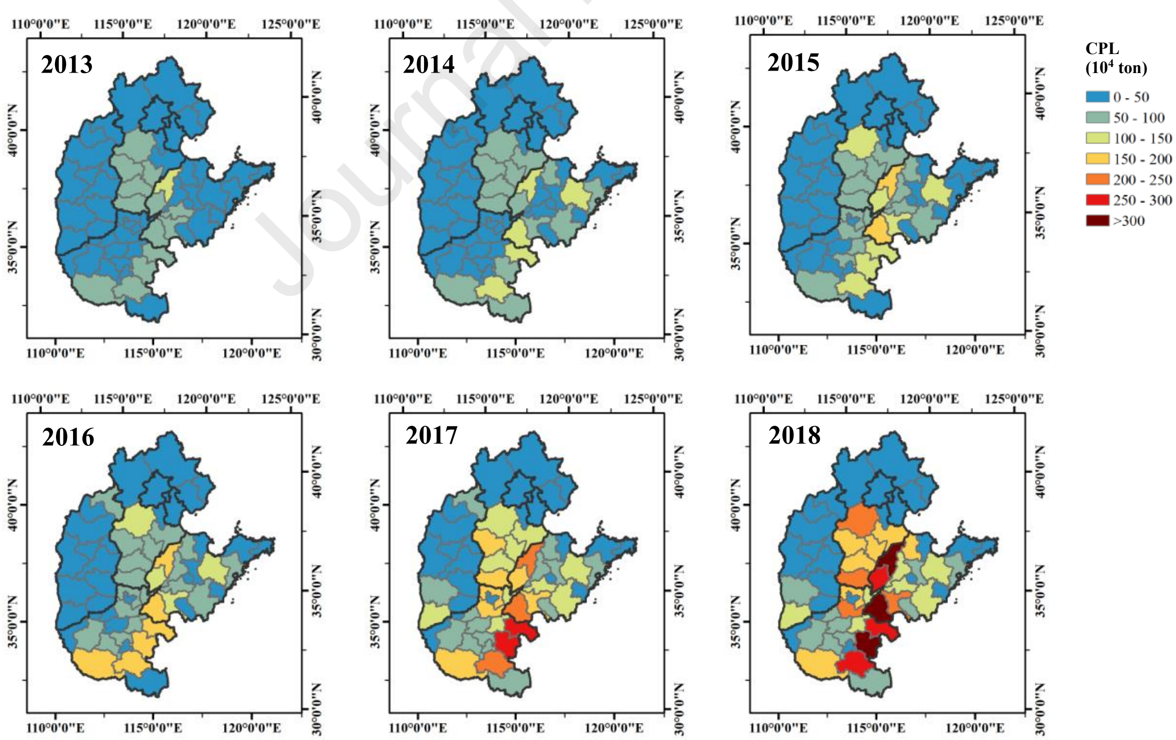

Figure 5. O_3-induced city-level crop production losses for winter wheat from 2013 to 2018.

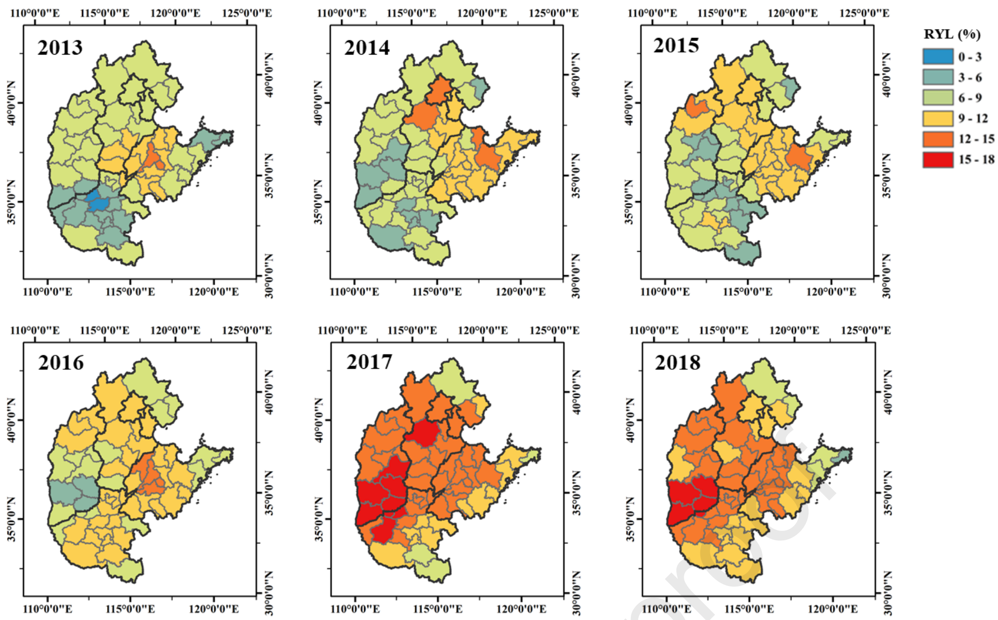

Figure 6. The estimated O_3-induced relative yield losses of summer maize from 2013 to 2018.

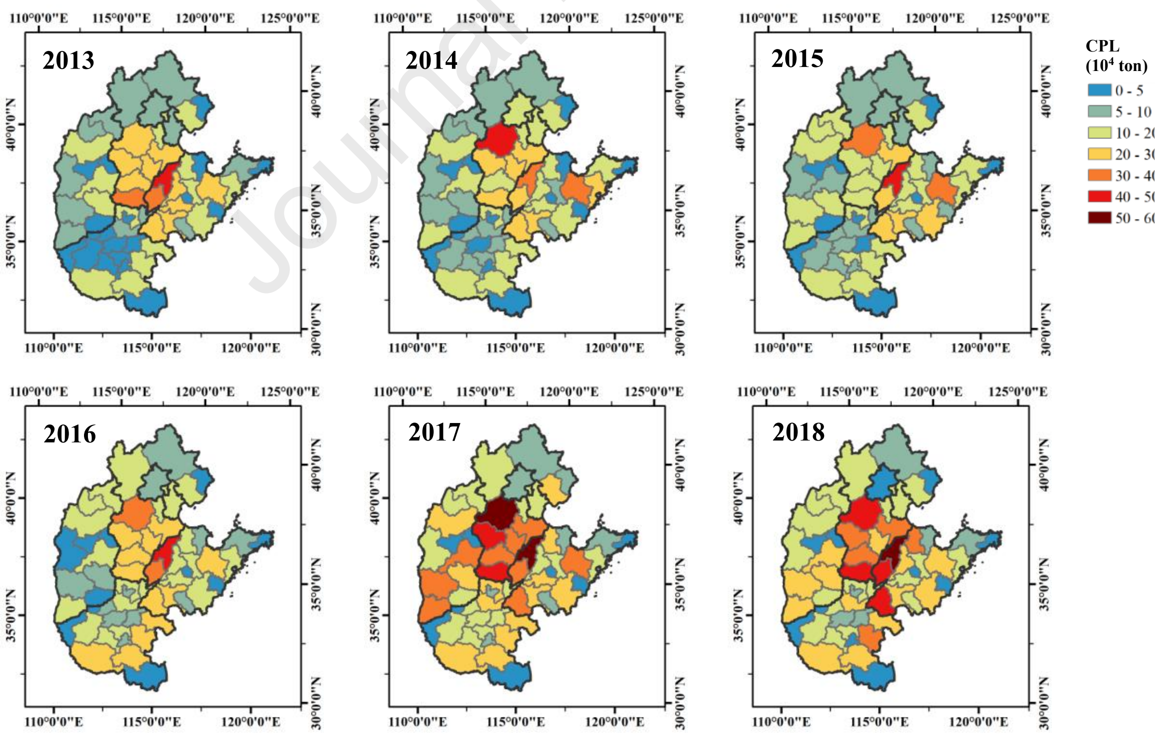

Figure 7. O_3-induced city-level crop production losses for summer maize from 2013 to 2018.

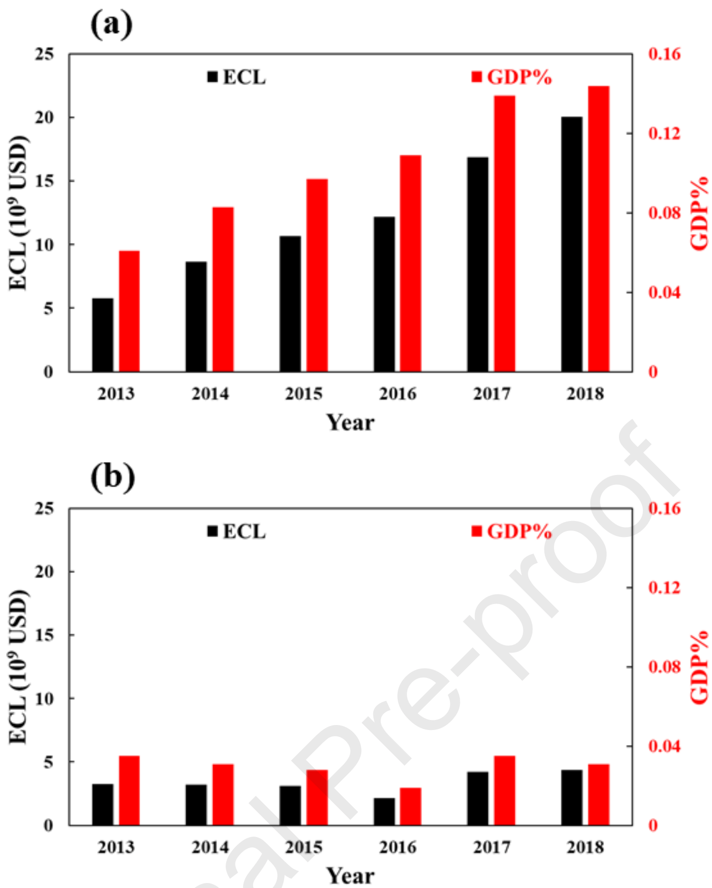

Figure 8. The estimated O_3-induced total economic cost losses of (a) winter wheat and (b) summer maize and losses as a percent of China GDP from 2013 to 2018.

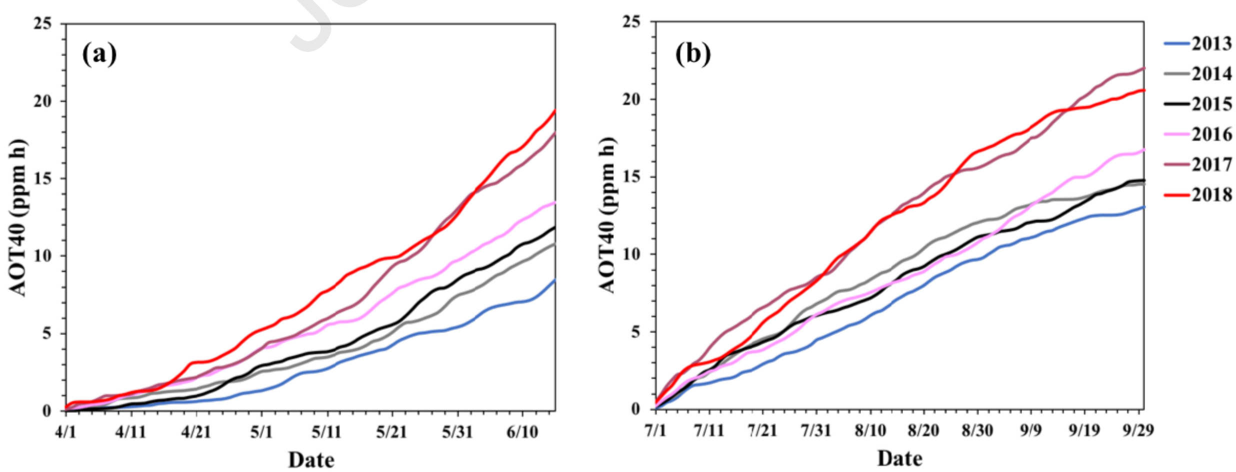

Figure 9. Evolution of the regional mean AOT40 during the growing period of (a) winter wheat and (b) summer maize from 2013 to 2018.

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.

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: