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Economic losses due to ozone impacts on human health, forest productivity and crop yield across China

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ABSTRACT

China's economic growth has significantly increased emissions of tropospheric ozone (O_3) precursors, resulting in increased regional O_3 pollution. We analyzed data from > 1400 monitoring stations and estimated the exposure of population and vegetation (crops and forests) to O_3 pollution across China in 2015. Based on WHO metrics for human health protection, the current O_3 level leads to +0.9% premature mortality (59,844 additional cases a year) with 96% of populated areas showing O_3–induced premature death. For vegetation, O_3 reduces annual forest tree biomass growth by 11–13% and yield of rice and wheat by 8% and 6%, respectively, relative to conditions below the respective AOT40 critical levels (CL). These CLs are exceeded over 98%, 75% and 83% of the areas of forests, rice and wheat, respectively. Using O_3 exposure–response functions, we evaluated the costs of O_3-induced losses in rice (7.5 billion US$), wheat (11.1 billion US$) and forest production (52.2 billion US$) and SOMO35–based morbidity for respiratory diseases (690.9 billion US$) and non–accidental mortality (7.5 billion US$), i.e. a total O_3-related cost representing 7% of the China Gross Domestic Product in 2015.

1. Introduction

After 40 years of rapid economic development, China has become the second largest economy of the world and the largest emitter of fossil fuel exhaust into the atmosphere with a significant adverse impact on environment (Boden et al., 2017). In recent years, China's smog pollution has become a growing prominent public concern around the world (Liu et al., 2016). The multi–contaminant ambient air pollution in China is at the higher end of the world air pollution level (Gao et al., 2011). For instance, the 90th percentile of daily maximum 8–hour ozone (O_3) concentrations increased from 91 ppb in 2013 to 101 ppb in 2015 in Beijing (BMEPB, 2015). Therefore, air pollution in China represents an unprecedented threat to human and vegetation health (Liu et al., 2016; Lelieveld et al., 2015; Tian et al., 2016). The adverse effects of alarming pollution levels in China have been estimated based on satellite data (Van Donkelaar et al., 2010; Verstraeten et al., 2015) and models (Lelieveld et al., 2015; Madaniyazi et al., 2016) for particulate matter, surface O_3, sulphur dioxide and nitrogen oxides (Liu et al., 2016; Rohde and Muller, 2015). These results report that 2.5 million people die every year from the health effects of indoor and outdoor air pollution in China (Lelieveld et al., 2015).

Ozone is a strong oxidant gas, which is estimated to kill > 0.7 Million people a year worldwide (Anenberg et al., 2010) and significantly affect crop yield (−14–26 billion US$) (van Dingenen et al., 2009) and forest biomass (−7%) (Wittig et al., 2009). Effects on human health include premature mortality due to cancer, respiratory and

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cardio–vascular diseases (WHO, 2013), while effects on plants include yield (Tang et al., 2013) and biomass decline (Wittig et al., 2009; Li et al., 2017). Besides, O_3 pollution is projected to be more damaging to global food production than climate change (Tai et al., 2014).

Based on epidemiological studies, the air quality guidelines of the World Health Organization (WHO) recommend 50 ppb O_3 as daily maximum 8–hour running average for human health protection (WHO, 2008). Other metrics were proposed in Europe e.g. SOMO35, i.e. the Sum of Ozone Means Over 35 ppb in the calendar year (Ellingsen et al., 2008). Globally, the most widely used index for the protection of vegetation against O_3 is AOT40, i.e. the accumulation of hourly O_3 concentrations above 40 ppb over the daylight hours during the growing season (Lefohn et al., 2018). For the calculation of AOT40, the United Nations Economic Commission for Europe recommends different species-specific time-windows and critical levels (CLs), i.e. the cumulative exposure below which no direct adverse effects on sensitive vegetation may occur according to present knowledge (UNECE, 2018). For ground–level O_3, China adopted in 2012 the Ambient Air Quality Standard for human health protection, with 50 ppb (special areas e.g. national parks) and 80 ppb (urban and industrial areas) as daily maximum 8–hour running average, and started reporting hourly O_3 values from a large number of monitoring stations (MEP, 2012). The standards took effect in many cities in Beijing–Tianjin–Hebei, Yangtze River Delta and Pearl River Delta regions since 2012 and at nation level since 2016. To date, a quantitative understanding of surface O_3 pollution effects on Chinese population mortality (Shang et al., 2013), crop yield (Carter et al., 2017) and forest productivity (Li et al., 2017, 2018) is limited. A recent study reported that the exposure of humans and vegetation to O_3 in China is greater than in other developed regions in the world (Lu et al., 2018) while an assessment of yield and economic losses for wheat and rice due to ground–level O_3 exposure was proposed from O_3 measurements in 24 cities of the Yangtze River Delta region (Zhao et al., 2018a, 2018b). To date an estimation of the total O_3–induced losses for China in terms of mortality, crop yield, forest production, and consequent economic losses, is missing. The spatial representativeness of air quality monitoring stations of the China's National Environmental Monitoring Center offers an unprecedented way to analyze surface O_3 pollution and estimate impacts.

This study aims to provide a quantitative estimate of O_3 risk to human and vegetation health in China in 2015 and estimate the relative economic losses based on real–time measurements, with focus on i) the most cultivated crops (rice and wheat, with 189 and 106 M tons of yield in 2015, respectively (FAO, 2016)), ii) the most represented forests (He et al., 2017) (broadleaf, $114 \times 10^4\,km^2$) and iii) exposed population. We then used these results to evaluate the predictive capacity of major modelling systems.

2. Methods

2.1. Data source and mapping

Hourly O_3 measurements in 2015 were obtained from 1497 stations (589 rural and 908 urban), after checking for data quality. A minimum data capture of 85% was imposed to calculate a valid aggregated value (e.g. AOT40, SOMO35). We used all the stations for both analyses of human impacts and vegetation impacts, because the difference of O_3 concentrations between rural and urban stations is negligible in this database as reported by Li et al. (2018). The measurements height of the stations was not available. Ozone metrics and relative values of yield/biomass were spatially interpolated by inverse weighting distance (IDW), to efficiently estimate surface air pollutant levels in areas where no measurements are available (Beelen et al., 2009), using ArcGIS 10. Areas with no stations were excluded from the analysis.

2.1.1. Estimation of the impacts on human health

Population at each grid (0.5 × 0.5°) was obtained from NASA Earth data (CIESIN, 2005), used to estimate population in 2015 on the basis of an expected 5% increase of people as observed in China between 2005 and 2015 (http://perspective.usherbrooke.ca/bilan/tend/CHN/fr/SP.POP.TOTL.html), and layered with O_3 data after interpolation by IDW (Selin et al., 2009). The number of daily premature deaths was calculated as Orru et al. (2013):

$$Cases_{O_3j}^{mortality} = M_0 \times P_j \times (e^{\beta_{O_3} \Delta_{O_3j}} - 1)$$

where M_0 is the baseline mortality rate, P_j is the number of exposed persons at the grid j, β_{O_3} is the Exposure–Response (E–R) function for O_3 (i.e. relative risk for all–cause mortality) and Δ_{O_3j} is the estimated excess exposure, i.e. the variation of O_3 concentration above the selected O_3 threshold for the grid j.

We adopted M_0 equal to 0.55% for all age groups (Nielsen and Ho, 2013) and a Relative Risk (RR) value of 1.003 (95% CI: 1.001, 1.004), based on the WHO meta–analysis, and corresponding to a 0.30% increase in daily premature mortality caused by a 5 ppb increase in the daily maximum 8–hour average O_3 concentration above the selected thresholds at each station (WHO, 2008). We used SOMO35 (in ppb days) i.e. the yearly sum of the daily maximum of 8–hour running average for O_3 over a threshold of 35 ppb in the calendar year, according to the European air quality guidelines (Ellingsen et al., 2008). In addition, we selected the number of exceedances of daily maximum 8–hour values (MDA8) > 50 ppb as recommended by WHO air quality guidelines (WHO, 2008) and 80 ppb as recommended by the Chinese air quality guidelines (MEP, 2012).

Costs related to premature deaths were defined according to the literature. The mean (100,429 US$), minimum (84,600 US$) and maximum (107,620 US$) values of the willingness to pay were calculated from data reported in literature (Zhang et al., 2008; Guo et al., 2010).

Ozone effects on morbidity were calculated by using the E–R functions and unit costs for the impact categories k (Table 1). The total annual variation in morbidity cases for each impact category k was calculated by summing up the daily variations at each sampling station j as:

$$Cases_{O_3j}^{morbidity_k} = ER_{O_3jk} \times P_j \times \Delta_{O_3j}$$

where ER_{O_3jk} refers to the E–R functions for O_3 and health–send outcome k (Table 1), Δ_{O_3j} is the variation of O_3 concentration above the selected O_3 threshold and P_j is the exposed population at the grid j. The additional cases were then multiplied for the expected cost per event expressed in US$ (Selin et al., 2009).

2.1.2. Estimation of the impacts on vegetation health

AOT40 is the European standard for the protection of vegetation (Directive 2008/50/CE) and is used also in America and Asia (Tang et al., 2013; Lefohn et al., 2018). The spatial distribution (Li et al., 2018) of forest types was obtained from a digitized Atlas of China's Vegetation, was produced in 2000 with a scale of 1:100,000. As the time of land-use changes use is not fast, we assumed that 15 years can be a good approximation for an estimation of the presence/absence of the vegetation categories at national level. Evergreen broadleaf forests (EBF) and deciduous broadleaf forests (DBF) were identified. The distribution of winter wheat and rice was obtained from the Agricultural

Table 1
Exposure–Response (E–R) functions and confidence–intervals (CI 95%) for entire age groups and different impact categories for ozone (Matus et al., 2012). The E–R functions for morbidity are measured in cases/(year person μg.m^{-3}).

Impact category	E–R function	CI (95%)	
Respiratory hospital admissions	3.54E−06	6.12E−07	6.47E−06
Respiratory symptoms days	3.30E−02	5.71E−03	6.03E−02
Asthma attacks	4.29E−03	3.30E−04	8.25E−03

Table 2
Dose–response relationships of relative yield (RY) or relative biomass (RB) versus AOT40, critical levels (CL) and accumulation time windows for different vegetation types in China.

Plant type	Equation and critical level	Experiment	Time window
Rice	RY = -0.0095xAOT40 + 1 CL = 5.3 ppm h	Open–top chambers (Wang et al., 2012)	45 days before flowering – 30 days after flowering. For global models, flowering assumed for all China at the day of the year (DOY) 192
Wheat	RY = -0.0228xAOT40 + 1 CL = 2.2 ppm h	Open–top chambers (Wang et al., 2012)	April 1st–June 15th
Broadleaf deciduous forest	RB = -0.0061xAOT40 + 0.99 CL = 8.2 ppm h	Open–top chambers (Büker et al., 2015)	April 1st–September 30th in temperate climate and year–long in (sub–)tropical climate

Meteorology Observation Network (AMON) charged by China Meteorological Administration. AMON monitors the growth development of eight crops including wheat and rice in the main planting areas, and meteorological factors.

Using hourly surface O_3 data during daylight (i.e. > 50 W/m^2 global radiation), we calculated AOT40 over species–specific time–windows (Table 2) for each monitoring station. Then, we interpolated AOT40 based on station site data to grid cells with a spatial resolution of 0.05° using IDW (Piao et al., 2003).

To estimate yield/biomass loss, we applied dose–response functions obtained from experimental observations (Table 2) and selected the CLs at 5% reduction of yield/biomass (UNECE, 2018). For wheat, whose distribution in China does not include tropical climate, the growing season was considered as a fixed time window from 1st of April till 15th of June (Zhu et al., 2011), i.e. 45 days before flowering to 30 days after flowering. For rice, whose cultivation area spans from cold temperate to tropical climate, we applied the same time window (45 days before flowering to 30 days after flowering as for wheat), but the flowering time varied according to the geographic distribution of the rice production area (Zhang et al., 2017).

For wheat and rice, we applied dose–response functions obtained from experimental observations in China (Wang et al., 2012) (Table 2). As knowledge about broadleaf forest responses to O_3 in China is insufficient, we selected the equation suggested for broadleaf deciduous forests in Europe (Büker et al., 2015) and diversified the time window depending on the local climate: year–long for tropical and sub–tropical areas dominated by evergreen broadleaf trees and 6 months (April 1st–September 30th) for temperate areas dominated by deciduous broadleaf trees (He et al., 2017). The estimation of the yield loss at national level was done by averaging the values of yield losses in the areas selected for each ecosystem type.

The yield- and biomass-based economic losses were estimated based on the market price given by FAOSTAT (www.faostat.org) and from Global Wood (www.globalwood.org). The cost for rice was estimated at 457.89 USD/ton and the cost for wheat was estimated at 376.99 USD/ton in the year 2015. The 2015 production of rice was around 189 million tons and the production of wheat was around 106 million ton. The cost for forests was estimated at 285 USD/m^3 and the total yield was around 2 billion of m^3. For forest biomass losses assessment, we used a mean cost (USD/m^3) based on all broadleaf tree species. A mean loss value was calculated across China by a Geographic Information System.

2.2. ACCMIP models

Projected changes in tropospheric O_3 vary among modelling systems. In the framework of the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP), 16 global chemistry models have been validated and used to evaluate projected changes in air quality worldwide (Lamarque et al., 2013; Sicard et al., 2017). All models simulate temporal and spatial evolution of stratospheric O_3, anthropogenic and natural emissions at global scale (e.g. non–methane volatile organic compounds, NOx from soils and lightning, and carbon monoxide from oceans and vegetation) and gaseous tropospheric chemistry, with various degrees of complexity. Here we focus on 8 global chemistry models as they provide hourly O_3 concentrations (Figs. 1S–8S). The different O_3 metrics are calculated in agreement with the calculations made for measured data, except for rice where a fixed time window is applied as an average flowering period all over China. ACCMIP models are not suited to provide reliable estimates over a single year, while they provide information on the mean state of the system around a reference period (Lin, 2007; Gleckler et al., 2008; Anav et al., 2013). Thus we assumed that the average of the runs over 2000–2010 is representative of the year 2015. Finally, we calculated the percent deviation of O_3 metrics estimated from ACCMIP models relative to those calculated from the measured data by using only the areas where a specific target (people, wheat, rice, evergreen or deciduous forests) occurred (see Supplementary information).

3. Results

3.1. Impacts of ozone on human health

The risk to Chinese population is similar when we use SOMO35 and WHO standard (Fig. 1A–D), while the Chinese standard (Fig. 1E–F) suggests lower risks. Large areas of China exceed the WHO (Fig. 1C) and Chinese standards (Fig. 1E) for human health protection. We found that 59%, 58% and 32% of population, respectively, are exposed to exceedances of 35, 50 or 80 ppb daily maximum 8–hour average. The exceedances are mainly located in North–Eastern China especially in case of SOMO35, but the higher number of premature deaths is found in the South–Eastern region, due to a higher number of inhabitants in this area, where the most important Chinese cities are located.

The expected increase in mortality rate varies from 0.42% to 1.11% depending on the selected metric, corresponding to 28,000 to 74,000 premature deaths due to O_3 pollution (Table 3). By using a RR value of 1.003 (95% CI: 1.001, 1.004), the increase of the mortality rate is estimated at 1.11% using SOMO35, 0.90% using the WHO standard and 0.42% using the Chinese standard for health protection.

3.2. Impacts of ozone on vegetation

Most of China is exposed to AOT40 values exceeding the CLs for the protection of rice (75%) and wheat (83%) (Fig. 2A–B). Although rice is more O_3–tolerant than wheat (5.3 vs. 2.2 ppm h CL, Table 2), the exceedances are comparable over the cultivation areas, resulting in similar reductions of yield relative to clean air, i.e. −8% and −6% averaged over the domain for rice and wheat, respectively (Fig. 2E–F).

The evergreen broadleaf forests of (sub–)tropical China show similar O_3 risk relative to the deciduous temperate forests of north–-central China because the growing season during which the formers are exposed to O_3 is longer (all year long vs. 6 months) but O_3 pollution is lower (Fig. 2C–D), so that annual forest tree biomass growth is similarly reduced by 13% and 11%, respectively (Fig. 2G–H). Also, the exceedances of the AOT40 critical levels are similarly distributed over space (98% of China for both), even though they are 1.3 times higher for evergreen forests (Fig. 3), due to longer growing season.

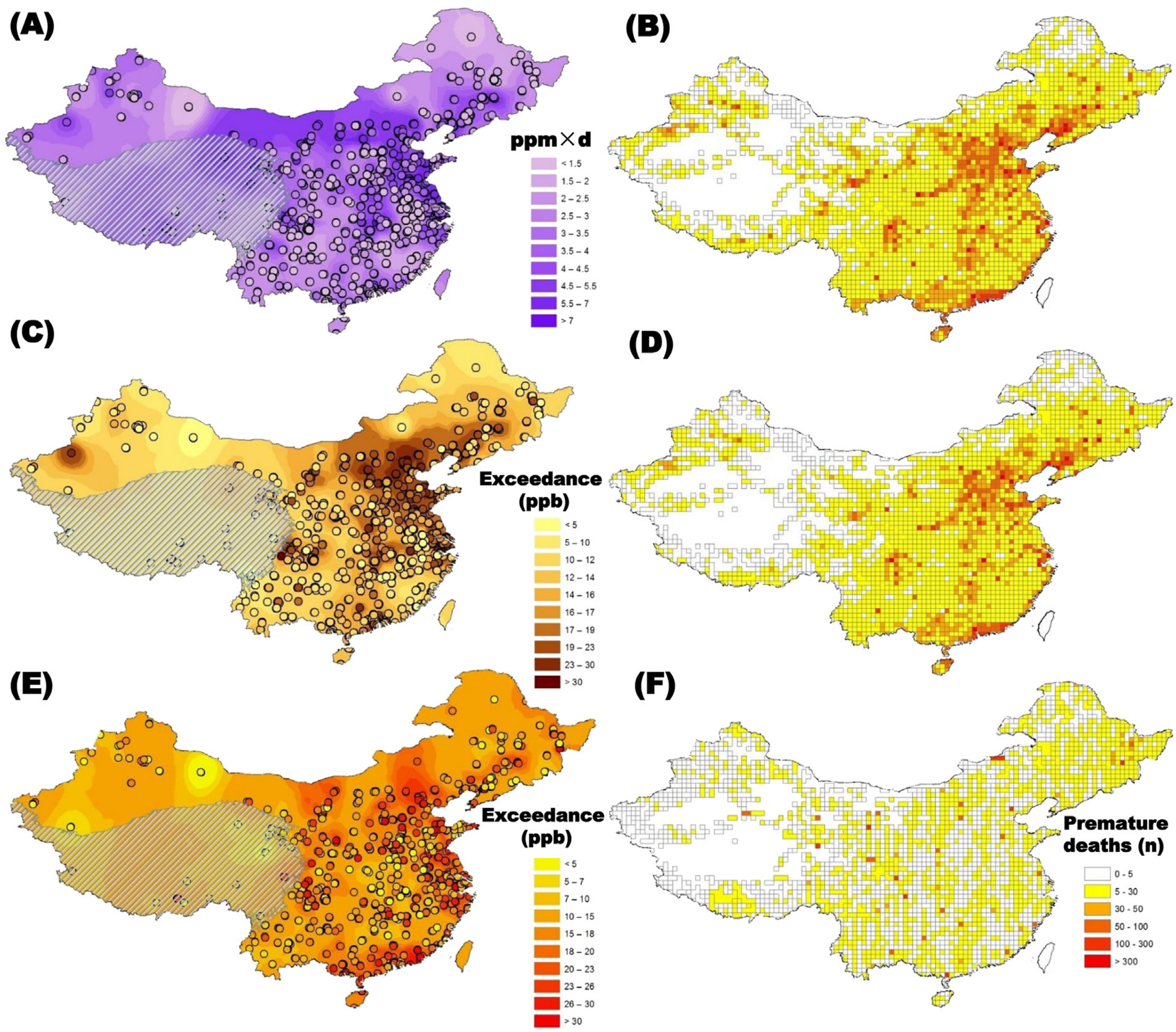

Fig. 1. Impacts of ozone pollution on Chinese population in 2015. Circles show measuring stations superimposed over a map obtained from inverse weighting distance for SOMO35 (A), WHO-based exceedance (C) and Chinese national standard (E), and related number of premature deaths due to ozone per grid based on exposed population (B, D, F). Grey hatchings indicate area not represented by local measuring stations.

3.3. Comparison of global models with results from measurements

When we compare our results with ACCMIP modelling estimates, the models show an underestimation of metrics for human health protection and an overestimation of metrics for vegetation protection (Fig. 3). The model uncertainties are lower when estimating by SOMO35, which is the metric with the lowest bias (Fig. 3). Percent differences range from −98% to +188% and increase with increasing threshold.

3.4. Economic losses due to ozone

For the first time, we performed an economic valuation of O_3 impacts on human health and vegetation (both forests and crops) from measured data in China. The losses range from 2.85 to 7.46 billion US dollars for the China standard and SOMO35, respectively (Table 3). Table 4 shows the estimates for economic losses due to O_3 pollution in terms of morbidity, thus in terms of hospital admissions for respiratory diseases and asthma attacks. The total costs are higher than the ones due to mortality and range between 265 and 690 billion US$ for the China standard and SOMO35, respectively.

Table 5 summarizes the costs of O_3 pollution due to losses in rice yield, wheat yield, forest production and SOMO35–based human health morbidity and mortality. About 90% of the total economic losses is due to human health effects, and about 6% is due to the losses in forest production. This value is twice higher than the costs due to crop (rice and wheat together) losses.

Table 3
Premature deaths, excess non–accidental mortality rates and relative costs (in billion US$) for different ozone metrics based on ozone measurements across China in 2015.

O_3 metric	Expected number of premature deaths (min – max)	Expected increase of mortality rate (min – max)	Costs (min – max)
SOMO35	74,316 (24,699–99,233)	1.11% (0.37%–1.48%)	7.46 (2.09–10.68)
WHO standard (50 ppb)	59,844 (19,903–79,883)	0.90% (0.30%–1.20%)	6.01 (1.68–8.60)
Chinese standard (80 ppb)	28,367 (9450–37,834)	0.42% (0.14%–0.57%)	2.85 (0.8–4.07)

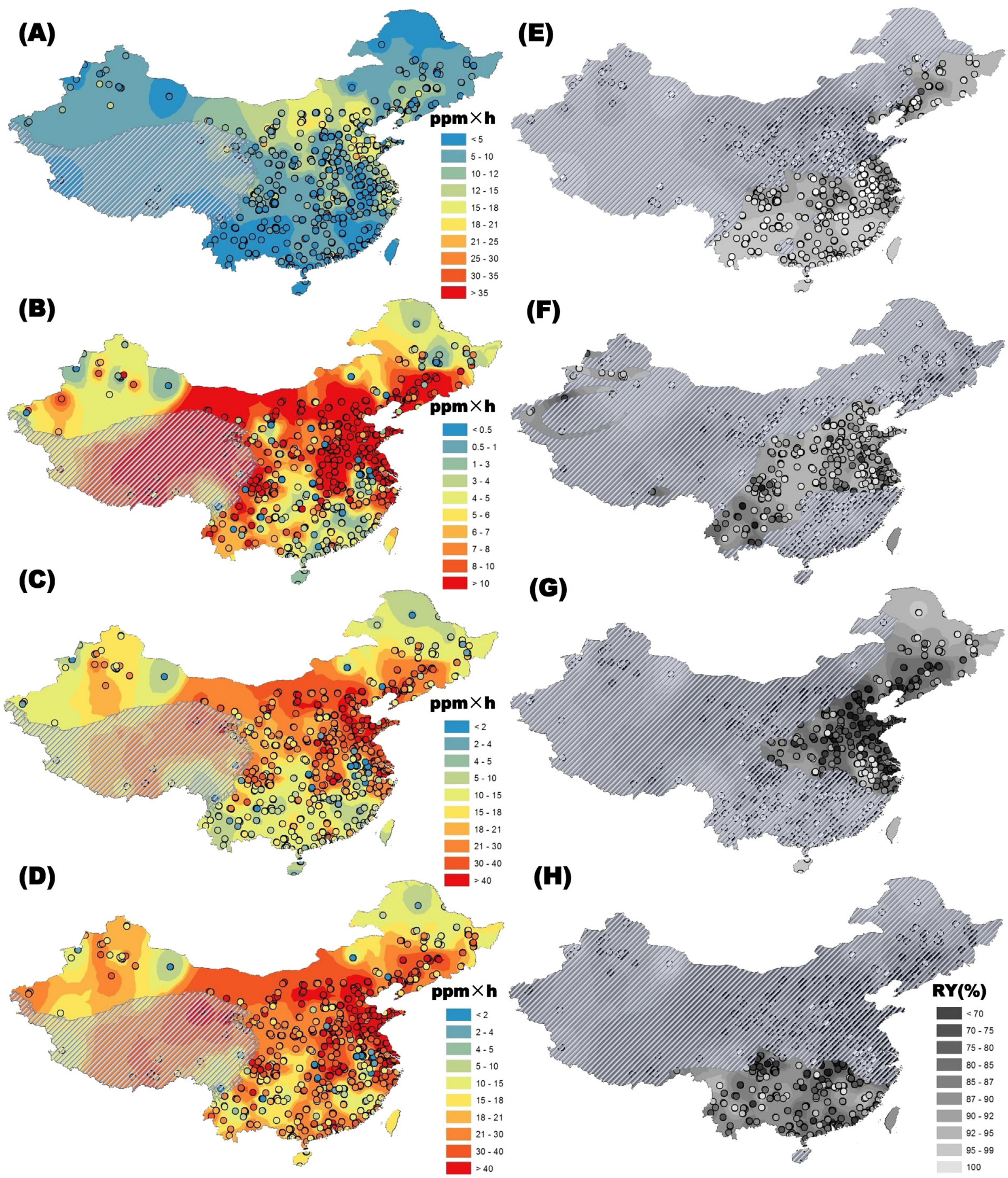

Fig. 2. Impacts of ozone pollution on Chinese vegetation in 2015. On left, AOT40 maps for rice (A, 45 days before and 30 days after actual flowering time in each pixel), winter wheat (B, April 1st–July 15th growing season), and broadleaf forests (C, deciduous forests, April 1st–September 30th; D, evergreen forests, year–long). On right, Percent Yield/Biomass relative to clean air (RY) for rice (E), winter wheat (F), deciduous broadleaf forests (G) and evergreen broadleaf forests (H). Circles show measuring stations superimposed on values from inverse weighting distance. Grey hatchings indicate areas not represented by local measuring stations (A, B, C, D) or not cultivated by rice (E) and winter wheat (F) or not covered by forests (G, H).

4. Discussion

Many epidemiological studies showed that surface O_3 can induce harmful health effects and mortality for cardio–vascular and respiratory diseases (WHO, 2013). Several studies analyzed the exposure–response relationship between O_3 and its effects on human health in major Chinese cities (Liu et al., 2016; Shang et al., 2013; Tao et al., 2012; Qian et al., 2006; Yin et al., 2017). Approximately 58% of Chinese population lives in areas with > 100 non–attainment days a year (MDA8 O_3 > 50 ppb), and 12% of the population is exposed to MDA8 O_3 > 80 ppb (WHO Interim Target 1) for > 30 days (Zhao et al., 2018a, 2018b). Two recent studies concluded that 1,143,000–1,163,000 premature deaths in China were attributed to ambient $PM_{2.5}$ and O_3 in 2010 accounting for about 12.0% of all–cause mortalities (Cohen et al., 2017; Gu et al., 2018).

We use the SOMO35 metric, widely used in Europe, in our

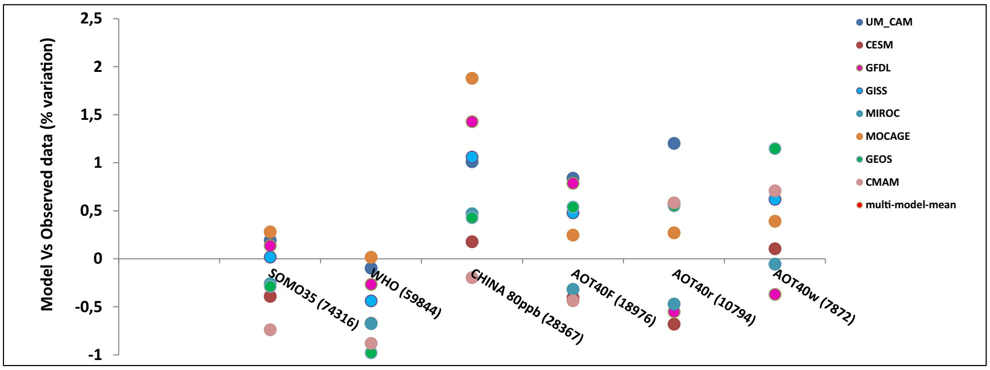

Fig. 3. Percent deviation of ozone metrics estimated from ACCMIP models relative to measurements. Numbers in parenthesis on the x axis are nation–wide averages in ppb day (SOMO35), ppb (WHO, Chinese standards) and ppb h (AOT40F, AOT40r and AOT40w stand for forests, rice and winter wheat, respectively). Overall, the models underestimate the risk for human health and overestimate the risk for vegetation.

Table 4
Costs of ozone–increased morbidity for respiratory diseases (in billion US$) in 2015.

O_3 metric	Hospital admissions (min – max)	Symptoms days (min – max)	Asthma attacks (min – max)	Total cost for respiratory diseases (min – max)
SOMO35	16.8 (2.9–30.7)	351.1 (60.7–641.5)	323.0 (28.4–621.1)	690.9 (88.5–1293.4)
WHO standard (50 ppb)	13.5 (2.3–24.7)	283.0 (49.0–517.1)	260.3 (20.0–500.7)	556.8 (71.3–1042.5)
Chinese standard (80 ppb)	6.4 (1.1–11.8)	134.5 (23.3–245.7)	123.7 (9.5–237.9)	264.6 (33.9–495.4)

Table 5
Costs of ozone pollution due to losses in rice, wheat, forest production and SOMO35–based human population health morbidity and mortality in the year 2015 in China.

Receptor	Cost (billion US$)
Rice	7.51
Wheat	11.09
Forests	52.25
Morbidity and mortality	698.36
Total	769.21

evaluations of the human health risks in China because SOMO35 is the most robust indicator for O_3 in global model calculations (Ellingsen et al., 2008), as confirmed by our results (Fig. 3). However, SOMO35 considers only acute health effects (e.g. lung inflammation, chronic obstructive pulmonary diseases (WHO, 2013) and does not account for possible chronic effects at long–term O_3 exposure levels below 35 ppb. We estimated 74,000 premature non–accidental deaths based on SOMO35. Recently, 270,900 premature deaths were estimated to be due to O_3 pollution in 2010 using a typical concentration–response function of O_3–induced mortality in log–linear form and city–specific RR for cardiovascular and respiratory mortality (Gu et al., 2018). Comparably with our results, the largest health impact attributed to O_3 pollution was observed in Eastern China, such as the Yangtze River Delta region and the Pearl River Delta region (Gu et al., 2018).

A meta–analysis of 33 epidemiological studies conducted in China, reported that an increase of 5 ppb of O_3 levels corresponded to a 0.45% (95% CI: 0.16, 0.73) increase in total non–accidental mortality over the time period 2000–2008 (Shang et al., 2013). A nationwide analysis, performed in 272 Chinese cities between 2013 and 2015, showed that a 5 ppb increase in MDA8 O_3 was associated with 0.24% (95% CI: 0.13, 0.35) increase in total non–accidental mortality (Yin et al., 2017) and with 0.37% (95% CI: 0.2, 0.55) increase in daily non–accidental mortality in 34 Chinese counties over the same study period (Sun et al., 2018). All these results are in line with the increase in non–accidental mortality of 0.42% for a 5 ppb increase in MDA8 O_3 obtained in this study. For comparison, a study of 23 European cities found a 0.34% (95% CI: 0.27, 0.50) increase in daily all–causes mortality associated with a 5 ppb increase in MDA8 O_3 (Gryparis et al., 2004).

Estimates of O_3 damages on forest productivity over the whole China region are limited. Due to the lack of monitoring data, previous attempts, to quantify the impacts of O_3 over China, relied on models and satellite data (Tang et al., 2013; Madaniyazi et al., 2016). To date, only one preliminary study, based on1500 monitoring stations across China, suggests that O_3 concentrations are seriously affecting forest productivity in China (Li et al., 2018) with large exceedance of metrics for forest protection (AOT40) in 2015. AOT40 exceeded the critical levels (5 ppm h) on average by 5.1 with a higher risk in northern China than in southern tropical and sub-tropical regions of China (Li et al., 2018). Key biodiversity areas in China were already identified as being at risk from high O_3 concentrations (Sicard et al., 2017). Because of the large gaps of knowledge regarding O_3 impacts on forests in China, the European dose-response function for broadleaf deciduous trees (Büker et al., 2015) was used to estimate the forest yield loss in this study. This is an assumption because the European dose-response functions are estimated on the basis of AOT40 cumulated over a six-month period (April–September) and we extended as year–long time period in (sub–) tropical climate. In addition, evergreen species are more O_3 tolerant than deciduous species (Calatayud et al., 2011; Li et al., 2017), then our approach may represent an overestimation of the O_3 impacts for subtropical areas.

Three studies (Tian et al., 2011; Ren et al., 2011; Yue et al., 2017) quantified the impacts of surface O_3 on carbon assimilation in China, either focused on net ecosystem exchange (Tian et al., 2011)[55] or on net primary productivity (NPP) (Ren et al., 2011; Yue et al., 2017). Elevated O_3 caused a 7.7% decrease in national carbon storage by forest ecosystems, with O_3–induced reductions in NPP ranging from 0 to −11.8% depending on forest types over the time period 1961–2005 (Ren et al., 2011). The reduction by O_3 pollution was equivalent to 7% of the net carbon sink in terrestrial ecosystems in China for the period 1961–2005 (Tian et al., 2011). The current O_3 levels reduce annual NPP by 14% on average (Yue et al., 2017). Based on AOT40, our results suggests that the annual forest tree biomass growth is reduced by 13% and 11% for evergreen broadleaf and deciduous broadleaf forests in China in 2015, relative to conditions below the respective AOT40 critical levels.

Wheat is an O_3–sensitive crop and rice is a moderately O_3–sensitive crop (Wang et al., 2012). It is well recognized that wheat and rice in Asia show a greater sensitivity to O_3 than that estimated by using the North American concentration–response relationships (Emberson et al., 2009). For instance, the concentration–response function for wheat is “*RY = -0.0228 x AOT40 + 1*” in China – as used in our study (Wang et al., 2012) – while “*RY = -0.0161 x AOT40 + 0.99*” is used in Europe (Mills et al., 2007).

Rice is one of the most important food crops for the world's population (Maclean et al., 2002). The demand for rice production will increase in the next decades due to the demographic growth, in particular in the major rice–consuming countries of Asia, Africa and Latin America (Maclean et al., 2002). Only 8% of global production of rice is traded internationally, i.e. the world price is very sensitive to small yield changes (Carter et al., 2017). The responses of rice production, exposed to increasing ground–level O_3, is thus of crucial importance for food security.

In this study, the O_3–related yield loss, relative to clean air, was 8% for rice and 6% for wheat as an average across China in 2015. Similarly, the relative yield loss (RYL) of wheat and rice based on AOT40, measured in 24 cities, ranged from 9.9 to 36.0% for wheat and 7.2–23.9% for rice in 2015 over the Yangtze River Delta (Zhao et al., 2018a, 2018b). A review of the impacts of surface O_3 on food crops in China concluded that the O_3 levels caused a wheat yield loss of 6.4%–14.9% in China in 2000 (Feng et al., 2015). From modelling estimates, the RYL was 19% for wheat and 4% for rice in China in 2000 (Van Dingenen et al., 2009). The difference among the studies can be attributed to the differing assumptions on O_3 metrics and dose–response functions (Avnery et al., 2011).

In terms of weight, wheat is the most O_3–affected crop, with a global loss of 45–82 M tons in 2000 and China accounts for 37% and 25% of the global rice and wheat RYL in 2000 (Van Dingenen et al., 2009). Based on AOT40 during the growing season, the global impact of surface O_3 on agricultural crops was evaluated for the year 2000 and showed that the current global RYL was significant for wheat (4 to 15%) but smaller (3–4%) for the more O_3–tolerant rice crop (Van Dingenen et al., 2009; Avnery et al., 2011). The O_3–induced wheat RYL was estimated in 2000 at 6–15% for China and 8–22% for India, based on AOT40 calculated over 90 days (3–month growing season) (Tang et al., 2013). In East Asia, surface O_3 levels in 1990 in China, Japan and South Korea induced losses by 1–9% of wheat and rice yield based on M7 and M12 exposure indices (Wang and Mauzerall, 2004).

For AOT40, a 1 ppm h incease is associated with a 1.59 ± 1.14% reduction in annual yield (Carter et al., 2017). The reduction was similar to that reported in a meta–analysis of non–FACE studies (Ainsworth, 2008), i.e. 14% decrease in yield for rice exposed to 63 ppb relative to charcoal–filtered air.

All the current estimation of the yield losses due to O_3 pollution are based on the O_3 concentrations, while is now recognized that O_3 uptake into the plants can be more appropriated to describe the O_3 impacts on vegetation (Sicard et al., 2016; De Marco et al., 2015, 2016). This approach for the moment cannot be applied in China due to the lack of meteorological information colocated with O_3 samplers. On the other hand, an estimation of the yield loss for wheat is available already by modelling approach (Mills et al., 2018), that demonstrated ozone impacts on wheat yield are particularly large in humid rain-fed and irrigated areas of major wheat-producing countries (e.g. United States, France, India, China and Russia).

Our estimation of yield loss are in general lower that the ones reported by model results, probably due to the overestimation that is generally associated to the global models, as demonstrated in Fig. 3.

The estimated health costs due to global O_3 pollution above preindustrial levels will be $580 billion by 2050 (Selin et al., 2009). The production losses for wheat and rice were estimated at US$3.5 billion and US$1.2 billion, respectively, in East Asia (Wang and Mauzerall, 2004) and at US$14–26 billion at the global scale (Van Dingenen et al., 2009). Few previous studies focused on the economic effects of O_3 at China's national level. The economic loss was estimated to 2.1 billion US$ for wheat (5.5 M tons) and 2.4 billion US$ for rice production (5.3 M tons) in 2015 in the Yangtze River Delta (Zhao et al., 2018a, 2018b). In 47 countries across Europe, loss in economic value for crop damage by O_3 exposure (based on production and sensitivity for 23 crops) was around US$ 8.4 billion in 2000 and US$ 5.6 billion in 2020 (Holland et al., 2006) and global crop production losses (79–121 M tons) were estimated at US$11–18 billion in 2000 and US$ 12–35 billion in 2030 depending on scenarios (Avnery et al., 2011).

In this study, the costs of losses in wheat (11.1 billion US$), rice (7.5 billion US$) and forest production (52.2 billion US$) due to O_3 pollution were estimated in 2015. The total O_3-related costs (769,21 billion US$) represent around 7% of the China Gross Domestic Product (GDP) in 2015. Our estimates are based on actual measurements of O_3 and are thus expected to be more robust than estimates based on models.

5. Conclusion

We found a significant overrun of exposure metrics (AOT40, human health metrics) in comparison with the objectives of legislative air quality directives. We conclude that O_3 air pollution threatens human health, food and wood productivity in China, the world's largest rice producer and importer (Carter et al., 2017) and the most popolous country in the world (Dudley and Chengrong, 2000). This impact is reflected in very high costs (7% of the China GDP in 2015). Such evidence–based knowledge is critical to inform decision–makers and public health authorities, and develop strategies for the protection of human and vegetation health from O_3. Further studies on the air pollution health effects in Chinese population are needed to define proper standards.

Declaration of Competing Interest

The authors declare no competing financial interests.

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Author contributions

Z.F., A.D.M., H.T. and E.P. conceived the project. Z.F., A.D.M., M.G., P.S. and F.T. provided new data and/or methods. A.A., A.D.M., P.S. and F.F. carried out modelling and analysis. All authors participated in writing of the manuscript, in particular A.D.M., E.P., P.S. and Z.F.

Appendix A. Supplementary data

Supplementary information is available in the online version of the paper. Correspondence and requests for materials should be addressed to A.D.M. Supplementary data to this article can be found online at doi:https://doi.org/10.1016/j.envint.2019.104966.

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