Earth's Future

RESEARCH ARTICLE
10.1029/2022EF002936

Marked Impacts of Pollution Mitigation on Crop Yields in China

Liyin He[1,2], Jing Wei[3], Yuan Wang[1,4], Quanbiao Shang[5], Junjie Liu[6], Yi Yin[1], Christian Frankenberg[1,6], Jonathan H. Jiang[6], Zhanqing Li[3], and Yuk L. Yung[1,6]

[1]Division of Geological and Planetary Sciences, California Institute of Technology, Pasadena, CA, USA, [2]Now at Department of Global Ecology, Carnegie Institution for Science, Stanford, CA, USA, [3]Department of Atmospheric and Oceanic Science and ESSIC, University of Maryland, College Park, MD, USA, [4]Now at Department of Earth, Atmospheric, and Planetary Sciences, Purdue University, West Lafayette, IN, USA, [5]Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, IL, USA, [6]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

Key Points:

- Robust crop yield prediction models are developed to assess climate change and air pollution impacts on agriculture
- During 2010–2018, the particulate pollution mitigation outweighs the negative impacts of concurrent climate change in China
- Exacerbated global warming will lead to crop yield reduction in spite of pollution alleviation in the future scenarios

Supporting Information:

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

Correspondence to:

Y. Wang,
yuanwang@purdue.edu

Citation:

He, L., Wei, J., Wang, Y., Shang, Q., Liu, J., Yin, Y., et al. (2022). Marked impacts of pollution mitigation on crop yields in China. *Earth's Future*, *10*, e2022EF002936. https://doi.org/10.1029/2022EF002936

Received 25 MAY 2022
Accepted 16 OCT 2022

Author Contributions:

Conceptualization: Yuan Wang
Data curation: Liyin He, Jing Wei
Formal analysis: Liyin He, Jing Wei, Yuan Wang, Quanbiao Shang, Junjie Liu, Yi Yin, Christian Frankenberg, Zhanqing Li, Yuk L. Yung
Investigation: Liyin He, Jing Wei, Yuan Wang
Methodology: Liyin He, Yuan Wang
Project Administration: Yuan Wang
Resources: Liyin He, Jing Wei, Yuan Wang

Abstract

Plant growth and crop harvest are impacted by both climate change and air pollution. However, their relative importance in crop yields remains elusive, especially in heavily polluted regions. Here we develop crop yield prediction models, based on a large volume of historical crop data, as well as climate and pollution records in China since 1980. A long-term surface ozone concentration data set is developed from a machine-learning model and various observations. An assessment of four climate and pollution factors reveals the critical role of particulate and ozone pollution in regulating interannual variations of crop yields in China. During 2010–2018, we find that the particulate pollution mitigation outweighs the negative impacts of concurrent climate change, resulting in 0.5%–1.9% net yield increases nationwide, despite of the ozone increases in the North China Plain. Looking to the future, the impacts of climate change, particularly from surface temperature increase, will dominate over pollution factors and profoundly reduce future maize and rice yields by 0.6 to 2.8% 10 yr^{-1} by 2050. Our findings call for attention on the threat to future global food security from the absence of pollution mitigation and the persistence of global warming.

Plain Language Summary

We capitalize on 39-year historical records of crop yields, climate variables, and pollution data to develop a robust crop yield prediction model. Utilizing this model, we show a critical role of particulate pollution in determining annual crop yields. Moreover, our analyses reveal that the recent abatement of anthropogenic emission in China results in a net crop gain, which masks the crop loss due to the increased temperature and precipitation. In the next 30 years, temperature dominant climate effects will emerge to steer the future trend of crop yields. The present study demonstrates the co-benefit of the recent air pollution control policy from agriculture and food perspectives. However, this benefit will eventually be diminished after the air pollution becomes alleviated in the full scale, while persisting or even exacerbated global warming will pose larger threat on the future food security.

1. Introduction

Crop yields are strongly influenced by regional climate and air quality (Wang et al., 2020). Temperature increase and resultant enhancement of the crop respiration have caused a global yield loss in recent decades (Lobell et al., 2011; Zhao et al., 2017), and such a trend is expected to be amplified over the next century as air temperature exceeds the tipping point in the crop-temperature relationship (Schlenker & Roberts, 2009). Precipitation exerts impacts on crop yield by altering soil and air moisture (Kimm et al., 2020) but in a non-monotonic manner (H. Li et al., 2019; Y. Li et al., 2019; Rosenzweig et al., 2002). Meanwhile, atmospheric pollutants such as anthropogenic aerosols and near-surface ozone exert detectable impacts on regional crop yields by changing physical, biochemical, and physiological processes during plant growth (Ainsworth, 2017; Chameides et al., 1999). Two of the pronounced aerosol effects on crop yields are the decrease in total solar radiation reaching the ground for plant photosynthesis (Gerstl & Zardecki, 1982) as well as the increase in diffuse radiation and light use efficiency (Hemes et al., 2020; Wang et al., 2021). The former is generally more significant, leading to a net negative effect (Tie et al., 2016). As a strong oxidant, ozone near the surface reduces photosynthesis by entering leaves via the stomata, producing damaging radicals, and consequently accelerating plant senescence (Felzer et al., 2007). Tropospheric ozone is mainly produced by photochemical reactions between nitrogen oxides (NO_x) and volatile

Supervision: Yuan Wang
Validation: Yuan Wang
Visualization: Liyin He, Yuan Wang
Writing – original draft: Liyin He, Yuan Wang
Writing – review & editing: Liyin He, Jing Wei, Yuan Wang, Quanbiao Shang, Junjie Liu, Yi Yin, Christian Frankenberg, Jonathan H. Jiang, Zhanqing Li, Yuk L. Yung

organic compounds in the presence of sunlight. Both precursor gases are of significant anthropogenic origin. On the global scale, regions with high levels of aerosol and ozone pollution are always collocated with croplands in rapidly developing countries. Therefore, effective controls of pollutant emissions in these regions have the great potential of alleviating crop yield loss due to air pollution (Burney & Ramanathan, 2014; Chameides et al., 1999). Meanwhile, it remains highly uncertain how air pollution and climate change compete or work together over the world's pollution centers with characteristic pollution evolutions in the past few decades (Wang et al., 2015).

China produces the largest amounts of rice and wheat in the world, and contributes approximately 28% and 17% of global production, respectively (Deng et al., 2019; H. Li et al., 2019; Y. Li et al., 2019). China is also the second-largest maize producer behind the United States, with more than an 18% share of production in the world maize economy (Meng et al., 2016). In the recent four decades, yields for staple crops in China have experienced decades of increases, mainly owing to technological innovation. Nevertheless, during the same period, there was about a 1°C increase in growing-season temperature over major crop regions globally, reducing relative yields by several percent (Zhao et al., 2017). The rapid urbanization, industrialization, and economic growth also led to serious regional haze in the majority of the country (Huang et al., 2015; Le et al., 2020). However, the recent decade starting from 2010 witnessed an unprecedented reduction in particulate pollution after a series of emission control policies and environmental protection laws by the Chinese government (Fan et al., 2020; Li, 2020; Sogacheva et al., 2018; Zhao et al., 2018). Particularly in 2013, China issued the nation's most stringent policy named as "Air Pollution Prevention and Control Action Plan." Since then, the particulate matter (PM) concentration has dropped by up to 50% (Zhang et al., 2019). Several studies using ground observations and crop models showed that yields significantly suffered from climate warming and increasing aerosols and surface ozone in northern and eastern China (Tie et al., 2016; Wang et al., 2007; Yi et al., 2018, 2020; Zhao et al., 2020). However, a systematic understanding of the crop yield response to climate and air pollution is limited due to the sparse and short records of ground observations.

This paper assesses the individual and joint impacts of climate and air pollution on both historical and future crop yields. We focus on three most important staple crops in China, including rice, maize, and wheat. A robust statistical model is established that accounts for the spatiotemporal variations of surface air temperature, precipitation, aerosol optical depth (AOD), and surface ozone (O_3) exposure, aiming to estimate the relative yield change (RYC) due to the individual and joint effects of those four factors. Similar yield models have also been used to study the response of yield to climate or pollution (Burney & Ramanathan, 2014; Butler et al., 2018; Hong et al., 2020; Lobell et al., 2011, 2020; McGrath et al., 2015; Tack et al., 2015). To our best knowledge, this study is the first effort to assess the yield benefit due to effective emission controls in China after 2010. We use long-term province-level yield annual reports with climate variables and air pollution data from various sources from 1980 to 2018. Lack of long-term surface ozone measurements has been an outstanding issue faced by large-scale data analysis studies. Here we employ the recently developed surface ozone data set in China, which is derived from a machine learning model that takes in ozone surface monitor data since 2013 as well as long term climate, emissions, and other auxiliary data set. Future yield changes by 2050 are assessed by feeding predicted climate and air pollution variations from the ensemble climate model projections to the established crop prediction models.

2. Materials and Methods

2.1. Observational Data

The annual crop production, harvested area, and yield data are from the National Bureau of Statistics of China (http://data.stats.gov.cn/). We use historical monthly temperature and total precipitation of 0.25° obtained from the fifth generation ECMWF reanalysis for the global climate and weather (ERA5) from 1980 to 2018 (Hersbach et al., 2019a, 2019b) The monthly surface maximum daily average 8 hr (MDA8) O_3 product of 0.1° × 0.1° is obtained from the China High Air Pollutants (CHAP) data set, which was predicted from the solar radiation intensity and surface temperature, together with other big data including observations, satellites, and models, by employing the space-time extremely randomized trees machine learning model (Wei et al., 2022). For surface ozone, we adopt a widely used MDA8 index to reflect ozone exposures on crops over the growing season. Such an index is highly correlated with the ozone cumulative index AOT40, which is a cumulative indicator of hourly ozone concentrations exceeding 0.04 ppm. Based on the ground-based observations, MDA8 ozone is highly correlated with AOT40 on the monthly basis, with R^2 of 0.92 (Appendix, Figure S1 in Supporting

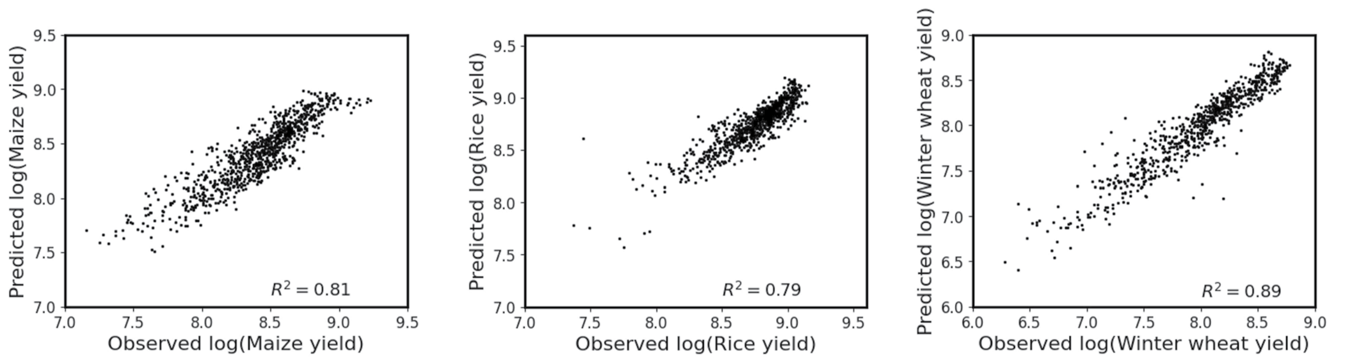

Figure 1. The correlation between predicted yield versus observed yield for maize (left), single-season rice (middle), and winter wheat (right).

Information S1). The historical monthly AOD at 550 nm data of 0.625 × 0.5° is obtained from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) (Global Modeling and Assimilation Office, 2015), as there is no satellite record providing continuing AOD measurements on the monthly basis since 1980. We validate the MERRA2 AOD by the retrieved AOD from AVHRR (Advanced Very High Resolution Radiometer) which is one of the earliest satellite instruments, whenever the product is available (Appendix, Figure S2 in Supporting Information S1). AOD measures the extinction of solar radiation by aerosol particles, for example, smoke, pollution, and dust. We hypothesize that aerosols exert impacts on crops mainly through the interference with atmospheric radiative fluxes, so the column-integrated quantity AOD is appropriate to be used in our analysis. The planted distribution of each crop at 10 km is generated by Spatial Production Allocation Model (SPAM) for 2010 (International Food Policy Research Institute, 2019). The crop distribution is then resampled to match the corresponding spatial resolution of temperature, precipitation, AOD, and surface ozone. The province-level observations of these four variables are averaged over grids with planted fraction greater than 2.5% of each crop.

2.2. Statistical Yield Model

To explore crop responses to various factors, we develop a statistical yield model for each crop using the following panel regression approach (Equation 1):

$$\begin{aligned}\log\left(\text{cropyield}_{i,y}\right) = \beta_0 + \beta_{\text{temp}} \cdot \text{temp}_{i,y} + \beta_{\text{precip}} \cdot \text{precip}_{i,y} + \beta_{\text{AOD}} \cdot \text{AOD}_{i,y} \\ + \beta_{O_3} \cdot O_{3\,i,y} + f_1(y) + f_2(i) + \varepsilon_{i,y}\end{aligned} \tag{1}$$

where temp, precip, AOD and O_3 are the growing-season averaged 2-m temperature, daily precipitation, AOD, and MDA8 O_3, respectively, during 1980–2018 (Appendix, Figure S3 in Supporting Information S1). Following the crop calendar for China reported by the United States Department of Agriculture, the growing season is defined as 3 months before the harvest season, which refers to June—August for single-season rice, July—September for maize and January—April for winter wheat. The subscripts i and y are indices for province and year. β_{temp}, β_{precip}, β_{AOD} and β_{O_3} are slope coefficients for each corresponding variable. β_0 is the regression intercept. We use the growing-season averaged climate and pollution variables instead of monthly averages to avoid the collinearity among monthly variables, which will lead to large uncertainty in the model fitting. There are steady increases in yearly yields throughout recent decades, which is likely due to the technological innovation in seeding, irrigation, and planting skills, as well as policy practices (Appendix, Figure S4 in Supporting Information S1). To account for the abovementioned time-varying factors contributing to the increasing yields, we introduce a set of yearly variables $f_1(y)$. In addition, to account for the spatial heterogeneity of some other impacts (e.g., soil and water qualities), provincial variables $f_2(i)$ are used. ε is the residual term.

We use *linearmodels* package in Python to fit the yield model, which also reports the significant levels (p-value) of regression coefficients and the model performance (R^2) (See details in Appendix, Table S1 in Supporting Information S1). The predicted crop yields by the regression models generally agree well with the reported yield (Figure 1), with the correlation coefficient square (R^2) being 0.79, 0.81, and 0.89 for rice, maize, and winter wheat, respectively. There are no obvious patterns between residuals versus fitted values, which validates the good performance of the chosen model (Appendix, Figure S5 in Supporting Information S1). It should be noted that our model assumes equal weight to different provinces regardless of their share in the national crop production. Therefore, our estimation is interpreted as an overall average impact.

We calculate 90% confidence intervals (CIs) of each coefficient. They are derived from the 5th and 95th percentiles by repeating the model 1,000 times using 75% bootstrap sampling of provinces for each year. We also use *dominance-analysis* package in Python to calculate the fractional contribution of different factors based on the residuals of the base model, which only includes yearly and provincial dummies. Dominance analysis calculates the dominance of one predictor over another by comparing their additional contributions to model performance in terms of R^2 across all subset models (Budescu, 1993).

2.3. Relative Yield Changes Due to Climate and Pollution Factors

We estimate (RYCs, unit: %) in 2006–2010 (or 2014–2018) compared to 1980–1984 (or 2006–2010) due to individual factors for the largest 10 production provinces of each crop. We choose 2010 as a breakpoint because of the increasing trend of AOD before 2010 and the reversed pattern afterward, which motivates us to quantify the different impacts of aerosol pollutants to crop yields before and after 2010. RYC is derived from the modeled yield difference between the predictors using the averaged historical level during 2006–2010 (or 2014–2018) and the hypothetical scenario with the same level during 1980–1984 (or 2006–2010). The 90% CIs of these RYC estimates are the 5th and 95th percentiles determined using the bootstrapping method, with 1,000 crop models generated from 75% observations each year.

The country-averaged yield predictions are estimated by the statistical yield model holding at the current technology stage, which is denoted as A0. To evaluate the contribution of a certain factor, we simulate the yield by fixing this factor at the same level as in 2015–2020, represented by A1. Then, we can isolate the corresponding contribution using the difference A1–A0. The uncertainty of future projections is obtained by resampling 1,000 times the yield model with bootstrapping from historical observations.

2.4. Possible Interaction Terms and Non-Linear Fitting in the Statistical Model

Previous literature have demonstrated that there may exist interactive relationships among the variables in our model (Burney & Ramanathan, 2014; Hong et al., 2020). For example, the change of temperature may positively affect the level of O_3, while AOD could decrease when precipitation increases due to the wash-out effect. Therefore, we add interaction terms in our base model (Equation 2), and the results are shown in Appendix, Table S2 in Supporting Information S1. There is no significant increase in R^2 after adding interaction terms across all three crops in Equation 2, implying the predictability cannot be enhanced by considering the two interactive relationships mentioned above.

$$\begin{aligned}\log\left(\text{cropyield}_{i,y}\right) = {} & \beta_0 + \beta_{\text{temp}} \cdot \text{temp}_{i,y} + \beta_{\text{precip}} \cdot \text{precip}_{i,y} + \beta_{\text{AOD}} \cdot \text{AOD}_{i,y} + \beta_{O_3} \cdot O_{3\,i,y} \\ & + \beta_{\text{inter1}} \cdot \left(\text{AOD}_{i,y} \times \text{precip}_{i,y}\right) + \beta_{\text{inter2}} \cdot \left(O_{3\,i,y} \times \text{temp}_{i,y}\right) + f_1(y) + f_2(i) + \varepsilon_{i,y}\end{aligned} \tag{2}$$

The second alternative model we choose is to add nonlinear trend variables into the regression (Equation 3). Instead of using yearly dummy variables, we test the model performance of representing the technological innovation and other time-varying effect as a combination of first and second order of polynomials regarding to year. The rationale is that these time-varying impacts may not be linear across years. When new technology is adopted to crop planting, its positive impact on RYC usually increases at first couple of years and then saturates. The corresponding results are presented in Appendix, Table S3 in Supporting Information S1. We find that the first order polynomial year variable is positive, indicating that the yield is increasing along the time. The quadratic year variable is negative for all crops, which implies that the increasing rate of the yield is becoming level off.

$$\begin{aligned}\log\left(\text{cropyield}_{i,y}\right) = {} & \beta_0 + \beta_{\text{temp}} \cdot \text{temp}_{i,y} + \beta_{\text{precip}} \cdot \text{precip}_{i,y} + \beta_{\text{AOD}} \cdot \text{AOD}_{i,y} \\ & + \beta_{O_3} \cdot O_{3\,i,y} + \beta_{\text{year}} \cdot y + \beta_{\text{year2}} \cdot y^2 + f(i) + \varepsilon_{i,y}\end{aligned} \tag{3}$$

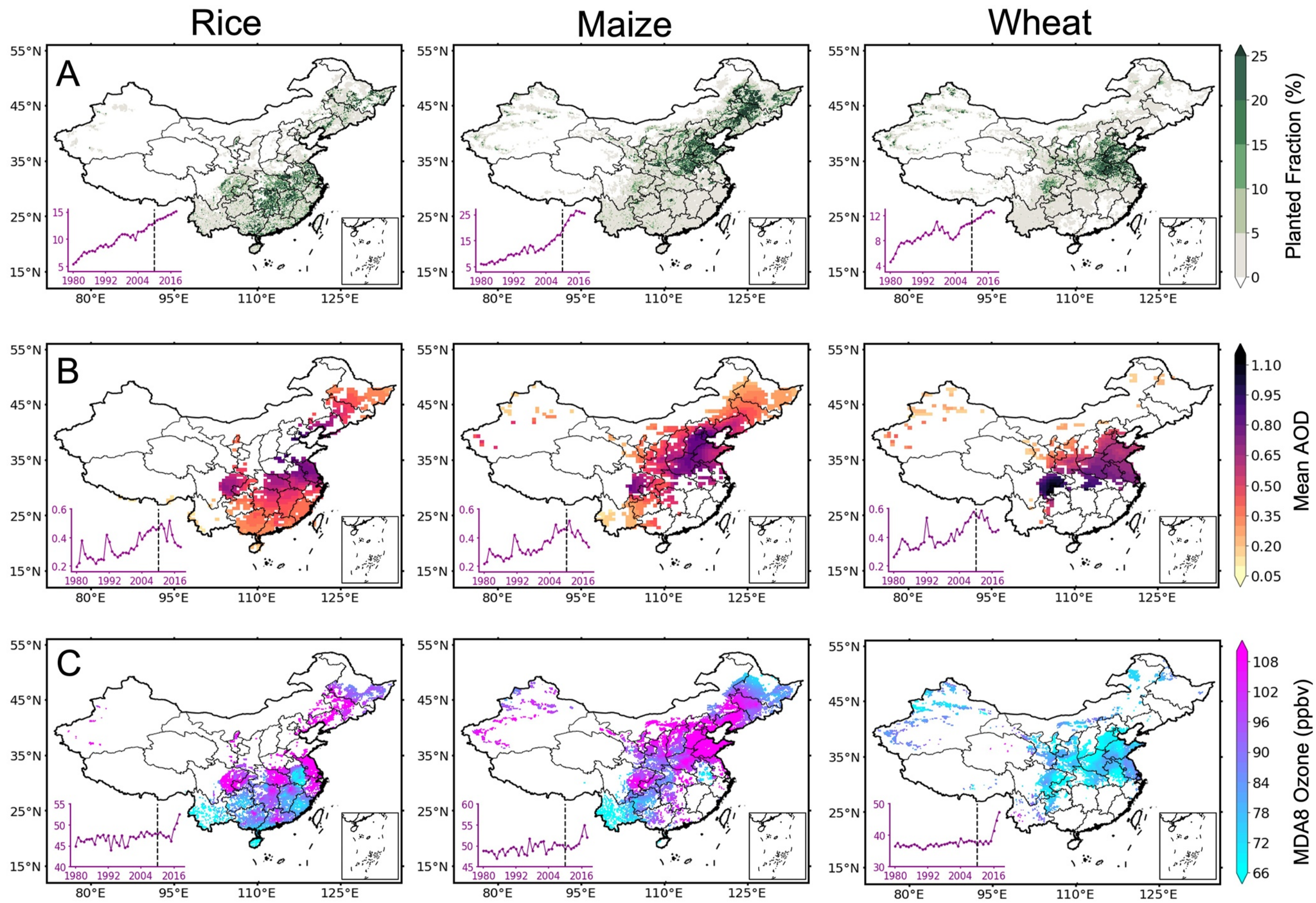

Figure 2. Geospatial maps and interannual trends of different crop types and corresponding pollution levels for peak growing seasons in China. (a) Planted fraction (unit: %) of each 10 × 10 km cell for rice (left), maize (middle) and wheat (right). (b) The climatology of MERRA2 aerosol optical depth (AOD) at 550 nm for peak growing seasons during 2006–2010. (c) The climatology of the surface ozone MDA8 for peak growing seasons during 2006–2010. The peak growing season is defined as June-August for rice, July-September for maize and January-April for winter wheat. The inserts show the times series of the total crop production (unit: × 10 Megatonnes) (a), AOD (b), and near surface ozone (c) for individual crop type during the peak growing season from 1980 to 2018. The time series of peak growing-season temperature, precipitation and annual total harvested area and country-averaged yields for three crops can be found in Appendix, Figure S7 in Supporting Information S1.

We find that these two alternative models do not make a significant difference in the model's predicting capability, lending support to the robustness of the modeled crop responses. To reduce the arbitrariness of the fitting form and to better interpret the result, we keep one variable in one term of the regression model.

3. Results

3.1. Historical Yield Response to Climate and Pollution Factors

Annual production and yields (production per area) of the three most important staple crops are analyzed in the 31 provinces of China from 1980 to 2018. There are two rice cropping systems in China, single-season, and double-season. The single-rice system (referred to as rice hereafter), which accounts for more than 65% of total rice production in China, is the main focus of our study. Figure 2a shows that a high planted fraction of rice is concentrated in southeastern China, particularly in the Yangtze River Basin. During 1980–2018, there is a quasi-linear increase in the rice production in China, which is believed to be mainly driven by the technological advancement (Peng et al., 2009). Maize is mainly planted in the North China Plain and Northeast of China (Figure 2a). The time evolution of total maize production exhibits two stages, and it experienced a faster increase in maize production after 2005 than before. Both spring wheat and winter wheat are planted in China, and winter wheat production accounts for around 90% of total China wheat production (Sun et al., 2018). The North

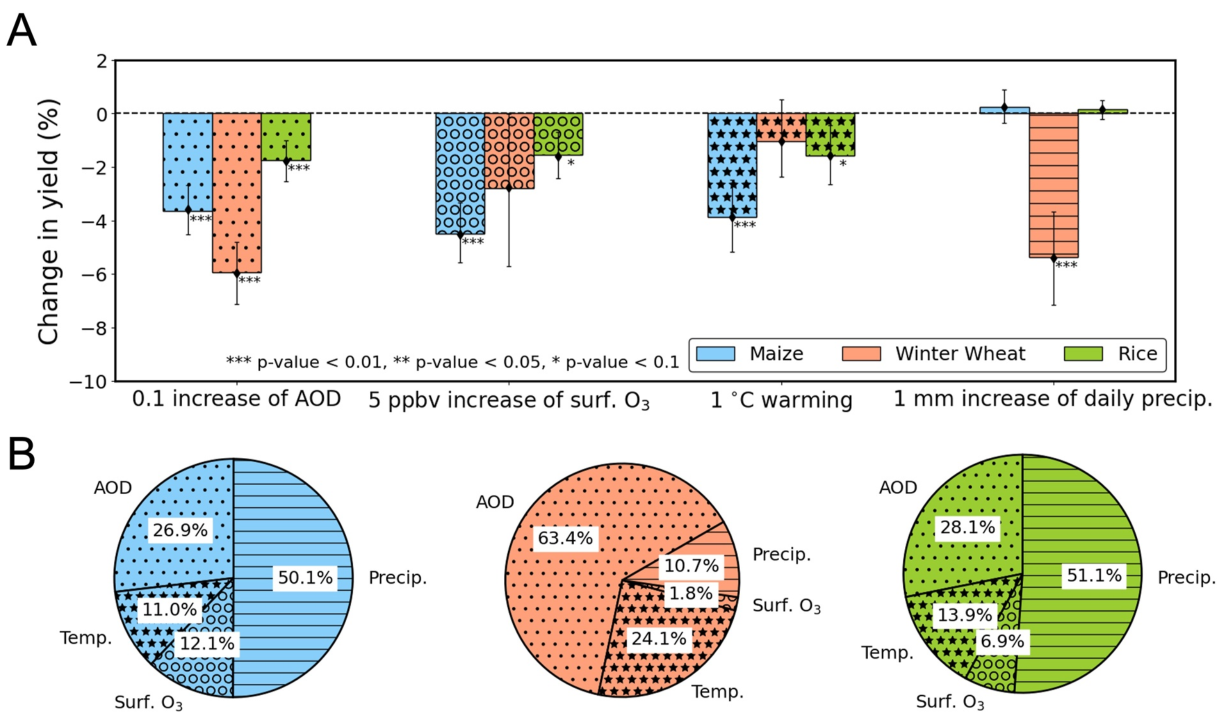

Figure 3. (a) Crop yield responses to air pollution and climate variations. The average yield response to unit change, that is, 0.1 increase of aerosol optical depth (AOD), 5 ppbv increase of surface zone, 1°C warming, and 1 mm increase of daily precipitation over the peak growing season from 1980 to 2018. The bar chart is plotted with diamond symbols (median estimates) and error bars (90% confidence intervals, CIs) by bootstrap resampling the model 1,000 times. (b) The percentage contribution of AOD, surface ozone, temperature, and precipitation to the spatial variations of yields for each crop using a dominance analysis. Blue, orange, and green color corresponds to maize, winter wheat, and rice, respectively.

China Plain is the major wheat planted area (Figure 2a), which produces more than 60% of total national wheat production (Lu & Fan, 2013). Even though the winter wheat total production also increased along with time, the earlier time period in the 1980 s had an even larger increase rate than in recent years. There was even a decline of production in the early 2000 s, due to the reduction in harvest area for winter wheat after 2000 (Appendix, Figure S4 in Supporting Information S1).

We further analyze spatial maps and temporal evolutions of the AOD and surface O_3 during the growing season of each crop type during 1980–2018. As shown in Figure 2b, the areas of high crop fractions are always accompanied by high AOD, such as the Yangtze River Basin for rice, North China Plain and Northeast China for maize, and central East China for wheat. The mean AOD during the growing season is 0.34, 0.35, and 0.42 for rice, maize, and wheat, respectively. Similarly, surface O_3 and crop fraction covary spatially, implying the potential influence of pollution on crop production. The mean MDA8 ozone during the growing season is 47.1, 49.7, and 37.8 ppbv for rice, maize, and wheat, respectively. The historical changes of AOD over different crop-dominant regions share the same key feature: a general increasing trend during 1980–2010, followed by a reduction in the recent decade. Such an AOD evolution characteristic reflects the implementations of emission control policies at different time periods in China. The trends of surface ozone are complicated (Figure 2c). Generally, there are small increasing trends before 2013, followed by an abrupt and steep increase since 2014. The most recent abrupt increases have been well observed (Lobell & Burney, 2021), but the main cause remains elusive, owing to the fact that O_3 production involving non-linear atmospheric chemistry can be at different regimes in urban and rural areas, and O_3 formation has a complex relationship with aerosols (Wu et al., 2020).

The crop yield models (Equation 1) derived from historical data show significant impacts from both air pollution and climate change (Figure 3). The crop yield is reduced by 1.7%–5.9% per 0.1 increase in AOD (Figure 3a), corroborating the hypothesis that particulate pollution reduces the solar radiation reaching the surface and lowers plant photosynthesis (Lobell & Burney, 2021; Tie et al., 2016). The winter wheat exhibits the largest sensitivity to particulate pollution, likely because northern China is more polluted in the wintertime when AOD variation is larger. Both maize and rice show significant yield reduction by ozone, and the reduction rate per 5 ppbv MDA8 ozone increase is larger for maize. The response of wheat to ozone bears a large uncertainty bar, likely due to the fact that the NCP, where wheat is mainly planted, experienced dramatic ozone change in recent years. A warmer near-surface air temperature results in yield loss for all crop types, with the largest response for winter wheat and the smallest and least significant sensitivity for rice. Our predicted magnitude of crop yield responses to temperature increase are consistent with previous assessments based on field warming experiments in China (Zhao et al., 2016) as well as a chemistry-crop-climate coupled model (Zhang et al., 2021). The crop responses to precipitation are complicated. Our result shows that every 1 mm precipitation per day can result in about 5.4% winter wheat yield loss during the growing season. Further analyses reveal that there are diverse responses of winter wheat to precipitation in the top six provinces in term of total yield. Our reduced regression models ran on individual provinces with time-fixed effects removed (Appendix, Table S4 in Supporting Information S1) show that, in the relatively wet provinces such as Anhui and Jiangsu in southern China, the precipitation has significantly negative impact on winter wheat yield (Li et al., 2010; Song et al., 2019). Precipitation provides moisture in the air and soil needed by plants, but is also accompanied with enhanced cloud cover and reduced radiation reaching the surface. Excessive precipitation can further cause devastating fungal pathogens for winter wheat near the end of the growing season (Wiik & Ewaldz, 2009). Such effects can be profound in Eastern China, since the end of the winter wheat growing season overlaps with the onset of the East Asian Summer Monsoon (Li et al., 2016). In contrast, maize and rice are less sensitive to precipitation changes, showing a small enhancement in yields.

To further reveal the relative importance of each factor with respect to the interannual variation of each crop, we conduct a dominance analysis and calculate the percentage contributions of different factors of interest to the residual of the base model. Among four targeted factors, precipitation is the most important one for maize and rice, accounting for about 50% of interannual variability in the detrended yield data (Figure 3b). The large fluctuation of precipitation over the agricultural regions in China are closely linked with the characteristics of East Asia Summer Monsoon, whose intensity is subject to many climate variabilities, such as El Niño–Southern Oscillation. Aerosol is the predominant factor for the winter wheat yield by explaining 63.4% of the interannual variability in the detrended data. Temperature and ozone pollution are relatively less important factors. Together, they can explain the rest 20%–25% variability. The results reinforce the notion that air pollution, particularly through anthropogenic aerosols, is crucial for crop production.

3.2. Agricultural Benefits From Pollution Mitigation After 2010

The year 2010 apparently represents a tipping point of particulate pollution in China because of the increasing/decreasing trend of AOD before/after that year. We focus on this recent pollution transition period and estimate RYC by different factors for the whole nation as well as the largest 10 production provinces of each crop. We group the responses to surface temperature and precipitation into the climate effect and the responses to AOD and ozone concentration into the pollution effect. RYC is calculated by the predicted yields under different hypothetical climate and pollution scenarios in our panel regression models. For example, to assess the influence of the recent pollution mitigation, we contrast the predicted crop yields using different AOD and ozone concentrations between two time periods, 2014–2018 and 2006–2010 and hold all other variables unchanged at the 2006–2010 levels. As shown in Figure 4, from 1980 to 2010, both climate and pollution factors resulted in the reduction of the yields, but the impact of pollution is more pronounced than that of climate variations. Three crop types generally share the same responses. Nationwide, pollution caused by the RYC is −4.8%, −8.5%, and −17.1% for rice, maize, and winter wheat, respectively, while climate induced RYC is only −1.4%, −1.8%, and −1.6% for three crops accordingly. The top 10 productive provinces for each crop also agree with each other on the signs of the effects but differ slightly in magnitude. In contrast, the effects of both pollution and climate were drastically changed in the second decade of the 21st century.

Owing to the effective emission control in China, the particulate pollution level significantly dropped in the growing seasons of three crops, resulting in increases in the national crop yield when comparing 2014–2018 to 2006–2010. However, due to the deteriorated ozone pollution after 2013 in the North China Plain, the crop yield gain by the PM mitigation was largely offset. Nationwide, the RYC induced by pollution mitigation is still positive, about 1.1%, 1.3%, and 2.4% for rice, maize, and wheat, respectively. For those provinces located in the North China Plain, such as Henan, Shandong, and Shanxi, a net reduction of maize yield by pollution factors is found after 2010, as the ozone pollution impacts outweigh that of the PM reduction. Climate-induced changes

10.1029/2022EF002936

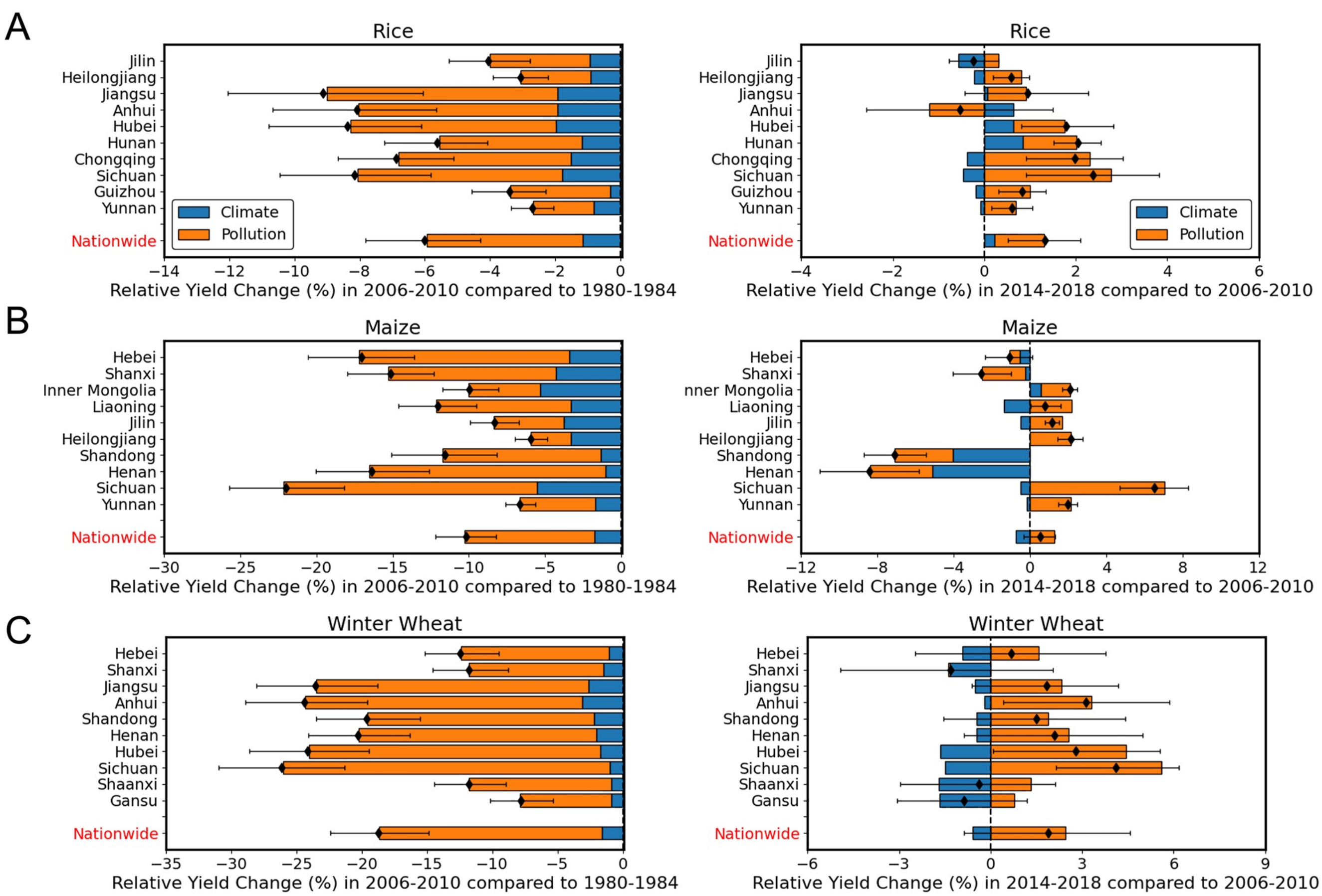

Figure 4. Relative yield change (RYC) attributed to climate and pollution changes for (a) rice (b) maize and (c) winter wheat. The climate change is the net effect of temperature and precipitation variations, and the pollution change concerns aerosol optical depth (AOD) and surface ozone together. For left panels, RYC is calculated as $(\text{Model}_{2006\text{–}2010\text{ avg}} - \text{Baseline}_{2006\text{–}2010\text{ avg}})/\text{Baseline}_{2006\text{–}2010\text{ avg}}$. $\text{Model}_{2006\text{–}2010\text{ avg}}$ is the estimated crop yield from the panel regression model using the historical 2006–2010 averaged climate and pollution records, and $\text{Baseline}_{2006\text{–}2010\text{ avg}}$ is estimated from the actual pollution (climate) levels but held with the same climate (pollution) scenario in 1980–1984. Nationwide changes are calculated as the sums of province values weighted by harvested areas. RYC is plotted as black diamonds (median estimates), with dark 5%–95% percentile error bars calculated by bootstrapping the model 1,000 times.

in crop yield during the same periods are insignificant for rice and winter wheat regions, leaving the pollution mitigation effects to dominate the crop yield variations. Most wheat-prevalent provinces experienced a moderate reduction in yield under climate change during 2006–2018, but the corresponding RYC is generally smaller than 2%. Overall, the reduction in aerosols in recent years stands out as a key driver of the crop variations on the interannual time scale.

3.3. Predicted Yield Changes by 2050

Capitalizing on the crop prediction models, we assess the impacts of future climate and pollution variations on the crop yields by 2050. Global climate simulations with various emission scenarios have been widely used to assess the societal and economic impacts by climate change (Shindell et al., 2021). Here the ensemble means of different models of Coupled Model Intercomparison Project (Phase 6, CMIP6) with the emission scenario SSP5-8.5 are used to reflect the future climate and pollution scenarios (Appendix, Figure S6–S8 and Table S5 in Supporting Information S1). The SSP5-8.5 represents the scenario with rapid and unconstrained growth with a fossil fuel-based economy, and will lead to ~2°C increase in global temperature in the 2050s compared to 1995–2014 (Li et al., 2018). The future projections aim to isolate the effects of temperature, precipitation, aerosol, and surface ozone levels on future yields under the assumption that the technology is held as equivalent to the current years (2015–2020). Note that hourly surface O_3 concentrations are not available from the CMIP6 models to calculate MDA8. According to the ground-based observations, O_3 MDA8 is linearly correlated with the O_3 monthly

10.1029/2022EF002936

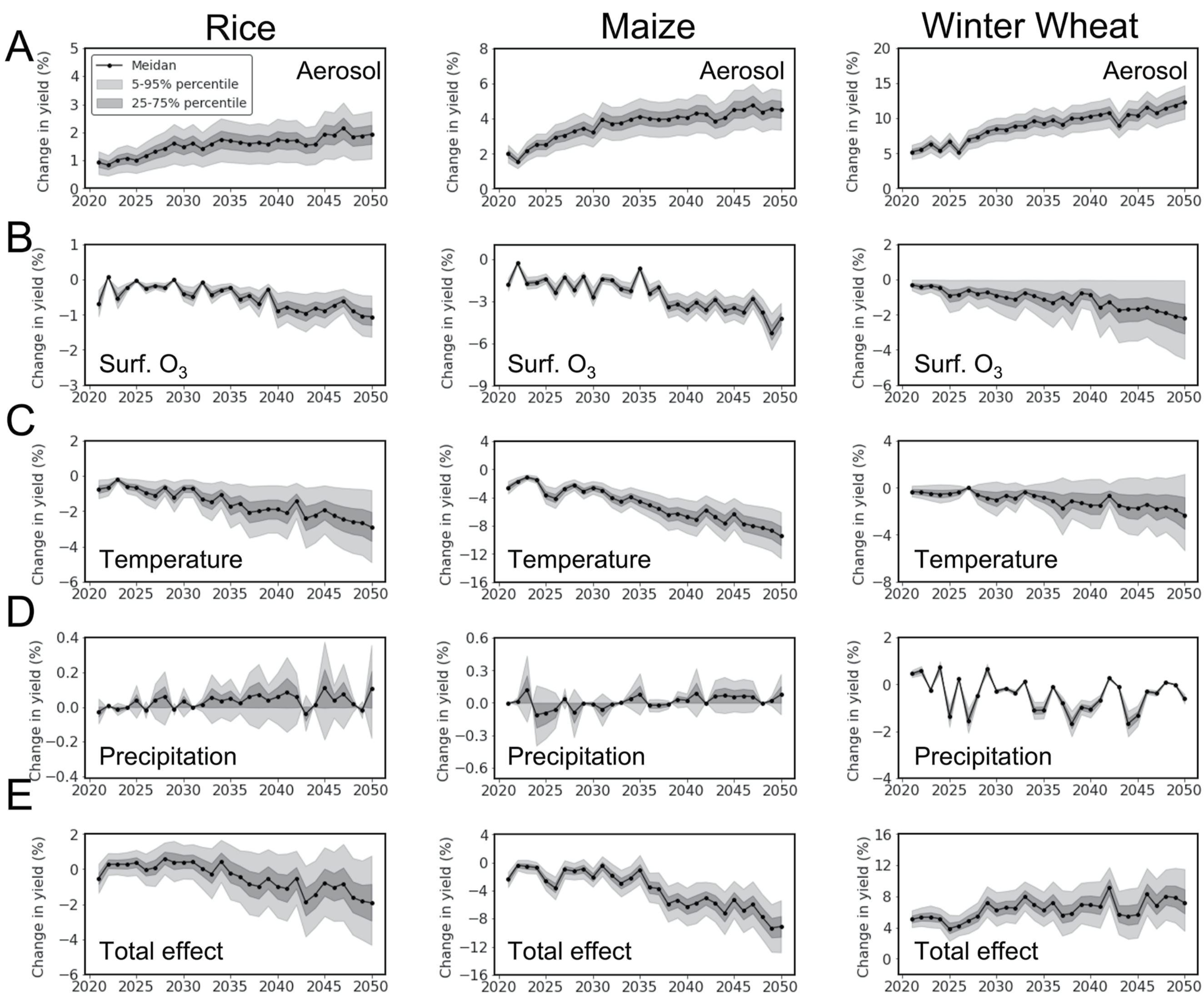

Figure 5. The projected future changes in country-level yield of rice, maize and winter wheat in response to (a) aerosol, (b) surface ozone (c) temperature (d) precipitation changes as well as (e) their total effects under RCP8.5. The future change in yield is estimated from the difference between projected growing-season climate or pollution scenarios in 2021–2050 and the averaged scenarios in 2015–2020. The yield change is plotted as points (median estimates), with dark and light shaded areas (25%–75% and 5%–95% percentile estimates) calculated by bootstrapping the model 1,000 times.

mean (MM) with R^2 at about 0.92 (Appendix, Figure S9 in Supporting Information S1), so we convert the O_3 MM in the CMIP6 model outputs to MDA8 following the empirical relationship: $\text{MDA8} = \text{MM} \times 1.3 + 6.2$.

Anthropogenic aerosols are projected to be continuously reduced in China by 2050. Thus, three crops all show a significant increasing trend in response to the aerosol variations (Figure 5a). Surface ozone level is projected to increase in the near future (Figure 5b), likely due to the reduction in the ozone precursor NO_x and consequent ozone enhancement via the non-linear ozone chemistry (Le et al., 2020) as well as the effect of temperature increase. For rice by 2050, the ozone-induced yield loss (−1.1%) is close to the aerosol-induced yield gain (+1.9%). Future temperature increase is found to be the most critical factor for all three crop types (Figure 5c). It can cause trends of −0.8%, −2.5%, and −0.6% per decade for rice, maize, and wheat, respectively. Future precipitation changes will not impose a noticeable influence on the crops (Figure 5d). Taking four factors together, for rice and maize, the temporal evolutions and trends under the total effects largely resemble those of the temperature changes during 2020–2050 (Figure 5e). Therefore, the regime shifts after 2020 in the way that the climate variability, particularly the global warming, dominates over the pollution factors and profoundly determines the future rice and maize yields. For winter wheat, as it exhibits large sensitivity to aerosols (Figure 3b), its net yield trend during 2020–2050 is positive, mainly determined by the future aerosol reduction.

10.1029/2022EF002936

4. Conclusion and Discussion

In the present study, we develop robust statistical models to predict three predominant crops in China, that is, rice, maize, and winter wheat. Four key factors are taken into account when predicting crop yields, including the temperature, precipitation, AOD, and surface ozone over the growing seasons. Time-varying factors contributing to the crop increases over the recent decades are also accounted for in the models, such as technological innovations and policy practices. To overcome the sparsity of the ground-level ozone observations over the 40-year time period, we employ a machine learning model and multiple sources of ozone, meteorological factors, as well as emissions since 1980. The ozone prediction from the machine-learning model is reliable according to the cross-evaluation by the reserved ozone measurements. The statistical models exhibit high fidelity in reproducing the yields of three prevalent crops in China. With moderate uncertainty, the models help us quantify the crop yield responses to different climate and pollution factors during different time periods in the past and future. We find the critical role of particulate pollution in regulating interannual variations of crop yields in China. Moreover, the recent abatement of anthropogenic emission results in a net crop gain, which masks the crop loss due to the increased temperature and precipitation.

The findings of alternative models with different mathematical formats are consistent with our main conclusions derived from previous model. Moreover, we assessed the collinearity of all variables in Appendix, Table S6 in Supporting Information S1. These correlations are not strong to undermine our conclusions. Overall, our findings in this alternative model are consistent with previous models, AOD and O_3 negatively affect RYC for all three crops.

Some other factors related to crop yield deserve further investigations, such as CO_2 fertilization effect and nitrogen deposition. With the elevated atmospheric CO_2 concentrations, plant photosynthesis and crop yield is expected to increase (Ainsworth & Long, 2004). Meanwhile, C3 crops (i.e., rice and wheat) typically show larger increase in water use efficiency than C4 crops (i.e., maize) with higher surrounding CO_2 concentrations. Meanwhile, nitrogen deposition is also likely to increase crop yields to a lesser extent (Lombardozzi et al., 2018). Additional reactive nitrogen has been produced due to human activities and contributed to the increase of terrestrial carbon sink (Wang et al., 2017). Since CO_2 concentrations and regional nitrogen availability has increased with time in the recent four decades, the yield benefit due to CO_2 fertilization and nitrogen deposition can then be captured by $f_1(y)$ in our statistical model. However, it remains unclear how the rate of CO_2 fertilization and nitrogen deposition will change in different regions in the future. Therefore, a better understanding of both effects in different cropping systems under various environmental conditions are needed to constrain our future predictions.

Our future predictions are based on historical response of crop yield to pollution and climate changes. Note that when the air becomes clean and background aerosol concentration becomes low, additional removal of aerosols may result in a negative effect on crop yield due to the absence of diffuse light fertilization. Such an effect may not be embedded in the historical data over certain regions. Also, some papers reported that the sensitivity of yield to drought is becoming larger accompanied with higher planting density under global warming (Lobell & Burke, 2008; Lobell et al., 2020). Meanwhile, the uncertainty in the future yield response to the warming is expected to be larger than precipitation due to the greater magnitude of temperature change relative to the year-to-year variations in precipitation (Lobell & Burke, 2008). Future studies are needed to combine yield and temperature data of different scales, that is, site and region, to explore explicitly the relationships between warming and yield to close the yield gap in the changing climate.

In summary, our finding demonstrates the co-benefit of the recent air pollution control policy from agriculture and food perspectives. However, such a benefit will be significantly offset or even outweighed by the exacerbated global warming. Hence, it will pose a great threat to global food security in the future, along with the growth of the world population. Our study calls for full consideration of air pollution impacts on the agriculture and crop yield on both interannual and decadal time scales when projecting future food production. Additionally, accurate long-term projections of particulate and ozone pollution are also in a pressing need to assess the future crop yield and to develop adaptation strategies.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The monthly temperature and precipitation products used in this study are publicly available at Copernicus Climate Change Service (https://cds.climate.copernicus.eu/cdsapp%23%21/dataset/reanalysis%2Dera5%2Dsingle%2Dlevels%2Dmonthly%2Dmeans%3Ftab%3Dform). The monthly aerosol optical depth (AOD) reanalysis product is available at Goddard Earth Sciences Data and Information Services Center (https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary). The monthly surface ozone data set is from the ChinaHighAirPollutants (CHAP) data set (https://zenodo.org/record/5765588#.Yo60MJPMK3I). The Spatial Production Allocation Model crop spatial distribution is available at https://s3.amazonaws.com/mapspam/2010/v2.0/geotiff/spam2010v2r0_global_phys_area.geotiff.zip. The annual province-level crop statistics are from National Bureau of Statistics of China (NBSC) (https://data.stats.gov.cn/english/adv.htm?cn=C01). NBCS requires registration to obtain a free account, then annual statistics report can be found in the search bar and downloaded as CSV files. The processed data used in this study and the code of our statistical models can be downloaded from https://doi.org/10.5281/zenodo.7232790.

Acknowledgments

Y.W. acknowledges the support of NSF (AGS-2103714). L.H. acknowledges the fellowship supported by the Resnick Sustainability Institute at California Institute of Technology. Y.W., J.L., C.F., J.H.J. and Y.L.Y. acknowledge the support of the Jet Propulsion Laboratory, California Institute of Technology, under contract with NASA. J.W. and Z.L. acknowledge the NASA Applied Science program (number: 80NSSC21K1980). We thank Drs. Xu Yue and Chao Liu for helpful discussions. All correspondence and requests for materials in this paper should be addressed to Y.W (yuanwang@purdue.edu).

References

Ainsworth, E. A. (2017). Understanding and improving global crop response to ozone pollution. *The Plant Journal*, *90*(5), 886–897. https://doi.org/10.1111/tpj.13298

Ainsworth, E. A., & Long, S. P. (2004). What have we learned from 15 years of free-air CO_2 enrichment (FACE)? A meta-analytic review of the responses of photosynthesis, canopy properties and plant production to rising CO_2. *New Phytologist*, *165*(2), 351–372. https://doi.org/10.1111/j.1469-8137.2004.01224.x

Budescu, D. V. (1993). Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression. *Psychological Bulletin*, *114*(3), 542–551. https://doi.org/10.1037/0033-2909.114.3.542

Burney, J., & Ramanathan, V. (2014). Recent climate and air pollution impacts on Indian agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(46), 16319–16324. https://doi.org/10.1073/pnas.1317275111

Butler, E. E., Mueller, N. D., & Huybers, P. (2018). Peculiarly pleasant weather for US maize. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(47), 11935–11940. https://doi.org/10.1073/pnas.1808035115

Chameides, W. L., Yu, H., Liu, S. C., Bergin, M., Zhou, X., Mearns, L., et al. (1999). Case study of the effects of atmospheric aerosols and regional haze on agriculture: An opportunity to enhance crop yields in China through emission controls? *Proceedings of the National Academy of Sciences of the United States of America*, *96*(24), 13626–13633. https://doi.org/10.1073/pnas.96.24.13626

Deng, N., Grassini, P., Yang, H., Huang, J., Cassman, K. G., & Peng, S. (2019). Closing yield gaps for rice self-sufficiency in China. *Nature Communications*, *10*(1), 1–9. https://doi.org/10.1038/s41467-019-09447-9

Fan, H., Zhao, C., & Yang, Y. (2020). A comprehensive analysis of the Spatio-temporal variation of urban air pollution in China during 2014–2018. *Atmospheric Environment*, *220*, 117066. https://doi.org/10.1016/j.atmosenv.2019.117066

Felzer, B. S., Cronin, T., Reilly, J. M., Melillo, J. M., & Wang, X. (2007). Impacts of ozone on trees and crops. *Comptes Rendus Geoscience*, *339*(11–12), 784–798. https://doi.org/10.1016/j.crte.2007.08.008

Gerstl, S. A. W., & Zardecki, A. (1982). Effects of aerosols on photosynthesis. *Nature*, *300*(5891), 436–437. https://doi.org/10.1038/300436a0

Global Modeling and Assimilation Office (GMAO). (2015). *MERRA-2 tavgM_2d_aer_Nx: 2d,Monthly mean,Time-averaged,Single-Level,Assimilation,Aerosol diagnostics V5.12.4*. Goddard Earth Sciences Data and Information Services Center (GES DISC). https://doi.org/10.5067/FH9A0MLJPC7N. Accessed: 07/10/2022.

Hemes, K. S., Verfaillie, J., & Baldocchi, D. D. (2020). Wildfire-smoke aerosols lead to increased light use efficiency among agricultural and restored wetland land uses in California's central valley. *Journal of Geophysical Research: Biogeosciences*, *125*(2), e2019JG005380. https://doi.org/10.1029/2019JG005380

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., et al. (2019a). ERA5 monthly averaged data on pressure levels from 1979 to present. *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. https://doi.org/10.24381/cds.6860a573

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., et al. (2019b). ERA5 monthly averaged data on single levels from 1979 to present. *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. https://doi.org/10.24381/cds.f17050d7

Hong, C., Mueller, N. D., Burney, J. A., Zhang, Y., AghaKouchak, A., Moore, F. C., et al. (2020). Impacts of ozone and climate change on yields of perennial crops in California. *Nature Food*, *1*(3), 166–172. https://doi.org/10.1038/s43016-020-0043-8

Huang, R. J., Zhang, Y., Bozzetti, C., Ho, K. F., Cao, J. J., Han, Y., et al. (2015). High secondary aerosol contribution to particulate pollution during haze events in China. *Nature*, *514*(7521), 218–222. https://doi.org/10.1038/nature13774

International Food Policy Research Institute. (2019). *Global spatially-disaggregated crop production statistics data for 2010 version 2.0"*. Harvard Dataverse. https://doi.org/10.7910/DVN/PRFF8V

Kimm, H., Guan, K., Gentine, P., Wu, J., Bernacchi, C. J., Sulman, B. N., et al. (2020). Redefining droughts for the US Corn Belt: The dominant role of atmospheric vapor pressure deficit over soil moisture in regulating stomatal behavior of Maize and Soybean. *Agricultural and Forest Meteorology*, *287*, 107930. https://doi.org/10.1016/j.agrformet.2020.107930

Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., & Seinfeld, J. H. (2020). Unexpected air pollution with marked emission reductions during the COVID-19 outbreak in China. *Science*, *369*(6504), 702–706. https://doi.org/10.1126/science.abb7431

Li, H., Zhou, Y., Xin, W., Wei, Y., Zhang, J., & Guo, L. (2019a). Wheat breeding in northern China: Achievements and technical advances. *Crop Journal. Crop Science Society of China/ Institute of Crop Sciences*, *7*(6), 718–729. https://doi.org/10.1016/j.cj.2019.09.003

Li, J. (2020). Pollution trends in China from 2000 to 2017: A multi-sensor view from space. *Remote Sensing*, *12*(2), 208. https://doi.org/10.3390/rs12020208

Li, S., Wheeler, T., Challinor, A., Lin, E., Ju, H., & Xu, Y. (2010). The observed relationships between wheat and climate in China. *Agricultural and Forest Meteorology*, *150*(11), 1412–1419. https://doi.org/10.1016/j.agrformet.2010.07.003

Li, X., Ting, M., & Lee, D. E. (2018). Fast adjustments of the Asian summer monsoon to anthropogenic aerosols. *Geophysical Research Letters*, *45*(2), 1001–1010. https://doi.org/10.1002/2017GL076667

Li, Y., Guan, K., Schnitkey, G. D., DeLucia, E., & Peng, B. (2019b). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global Change Biology*, *25*(7), 2325–2337. https://doi.org/10.1111/gcb.14628

Li, Z., Lau, W. M., Ramanathan, V., Wu, G., Ding, Y., Manoj, M. G., et al. (2016). Aerosol and monsoon climate interactions over Asia. In *Reviews of geophysics*. Blackwell Publishing Ltd. https://doi.org/10.1002/2015RG000500

Lobell, D. B., & Burke, M. B. (2008). Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environmental Research Letters*, *3*(3), 034007. https://doi.org/10.1088/1748-9326/3/3/034007

Lobell, D. B., & Burney, J. A. (2021). Cleaner air has contributed one-fifth of US maize and soybean yield gains since 1999. *Environmental Research Letters*, *16*(7), 74049. https://doi.org/10.1088/1748-9326/ac0fa4

Lobell, D. B., Deines, J. M., & Di Tommaso, S. (2020). Changes in the drought sensitivity of US maize yields. *Nature Food*, *1*(11), 729–735. https://doi.org/10.1038/s43016-020-00165-w

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, *333*(6042), 616–620. https://doi.org/10.1126/science.1204531

Lombardozzi, D. L., Bonan, G. B., Levis, S., & Lawrence, D. M. (2018). Changes in wood biomass and crop yields in response to projected CO_2, O_3, nitrogen deposition, and climate. *Journal of Geophysical Research: Biogeosciences*, *123*(10), 3262–3282. https://doi.org/10.1029/2018JG004680

Lu, C., & Fan, L. (2013). Winter wheat yield potentials and yield gaps in the North China Plain. *Field Crops Research*, *143*, 98–105. https://doi.org/10.1016/j.fcr.2012.09.015

McGrath, J. M., Betzelberger, A. M., Wang, S., Shook, E., Zhu, X. G., Long, S. P., & Ainsworth, E. A. (2015). An analysis of ozone damage to historical maize and soybean yields in the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(46), 14390–14395. https://doi.org/10.1073/pnas.1509777112

Meng, Q., Chen, X., Lobell, D. B., Cui, Z., Zhang, Y., Yang, H., & Zhang, F. (2016). Growing sensitivity of maize to water scarcity under climate change. *Scientific Reports*, *6*(1), 1–7. https://doi.org/10.1038/srep19605

Peng, S., Tang, Q., & Zou, Y. (2009). Current status and challenges of rice production in China. *Plant Production Science*, *12*(1), 3–8. https://doi.org/10.1626/pps.12.3

Rosenzweig, C., Tubiello, F. N., Goldberg, R., Mills, E., & Bloomfield, J. (2002). Increased crop damage in the US from excess precipitation under climate change. *Global Environmental Change*, *12*(3), 197–202. https://doi.org/10.1016/s0959-3780(02)00008-0

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(37), 15594–15598. https://doi.org/10.1073/pnas.0906865106

Shindell, D., Ru, M., Zhang, Y., Seltzer, K., Faluvegi, G., Nazarenko, L., et al. (2021). Temporal and spatial distribution of health, labor, and crop benefits of climate change mitigation in the United States. *Proceedings of the National Academy of Sciences*, *118*(46). https://doi.org/10.1073/pnas.2104061118

Sogacheva, L., Rodriguez, E., Kolmonen, P., Virtanen, T. H., Saponaro, G., De Leeuw, G., et al. (2018). Spatial and seasonal variations of aerosols over China from two decades of multi-satellite observations - Part 2: AOD time series for 1995-2017 combined from ATSR ADV and MODIS C6.1 and AOD tendency estimations. *Atmospheric Chemistry and Physics*, *18*(22), 16631–16652. https://doi.org/10.5194/acp-18-16631-2018

Song, Y., Linderholm, H. W., Wang, C., Tian, J., Huo, Z., Gao, P., et al. (2019). The influence of excess precipitation on winter wheat under climate change in China from 1961 to 2017. *Science of the Total Environment*, *690*, 189–196. https://doi.org/10.1016/j.scitotenv.2019.06.367

Sun, S., Yang, X., Lin, X., Sassenrath, G. F., & Li, K. (2018). Winter wheat yield gaps and patterns in China. *Agronomy Journal*, *110*(1), 319–330. https://doi.org/10.2134/agronj2017.07.0417

Tack, J., Barkley, A., & Nalley, L. L. (2015). Effect of warming temperatures on US wheat yields. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(22), 6931–6936. https://doi.org/10.1073/pnas.1415181112

Tie, X., Huang, R. J., Dai, W., Cao, J., Long, X., Su, X., et al. (2016). Effect of heavy haze and aerosol pollution on rice and wheat productions in China. *Scientific Reports*, *6*(1), 1–6. https://doi.org/10.1038/srep29612

Wang, R., Goll, D., Balkanski, Y., Hauglustaine, D., Boucher, O., Ciais, P., et al. (2017). Global forest carbon uptake due to nitrogen and phosphorus deposition from 1850 to 2100. *Global Change Biology*, *23*(11), 4854–4872. https://doi.org/10.1111/gcb.13766

Wang, X., Manning, W., Feng, Z., & Zhu, Y. (2007). Ground-level ozone in China: Distribution and effects on crop yields. *Environmental Pollution*, *147*(2), 394–400. https://doi.org/10.1016/j.envpol.2006.05.006

Wang, X., Wang, C., Wu, J., Miao, G., Chen, M., Chen, S., et al. (2021). Intermediate aerosol loading enhances photosynthetic activity of croplands. *Geophysical Research Letters*, *48*(7), e2020GL091893. https://doi.org/10.1029/2020gl091893

Wang, X., Zhao, C., Müller, C., Wang, C., Ciais, P., Janssens, I., et al. (2020). Emergent constraint on crop yield response to warmer temperature from field experiments. *Nature Sustainability*, *3*(11), 908–916. https://doi.org/10.1038/s41893-020-0569-7

Wang, Y., Jiang, J. H., & Su, H. (2015). Atmospheric responses to the redistribution of anthropogenic aerosols. *Journal of Geophysical Research: Atmospheres*, *120*(18), 9625–9641. https://doi.org/10.1002/2015JD023665

Wei, J., Li, Z., Li, K., Dickerson, R. R., Pinker, R. T., Wang, J., et al. (2022). Full-coverage mapping and spatiotemporal variations of ground-level ozone (O_3) pollution from 2013 to 2020 across China. *Remote Sensing of Environment*, *270*, 112775. https://doi.org/10.1016/j.rse.2021.112775

Wiik, L., & Ewaldz, T. (2009). Impact of temperature and precipitation on yield and plant diseases of winter wheat in southern Sweden 1983-2007. *Crop Protection*, *28*(11), 952–962. https://doi.org/10.1016/j.cropro.2009.05.002

Wu, J., Bei, N., Hu, B., Liu, S., Wang, Y., Shen, Z., et al. (2020). Aerosol–photolysis interaction reduces particulate matter during wintertime haze events. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(18), 9755–9761. https://doi.org/10.1073/pnas.1916775117

Yi, F., Jin, F., Jao, W., jun, Y., & Jiang, F. (2020). Influence of surface ozone on crop yield of maize in China. *Journal of Integrative Agriculture*, *19*(2), 578–589. https://doi.org/10.1016/S2095-3119(19)62822-4

Yi, F., McCarl, B. A., Zhou, X., & Jiang, F. (2018). Damages of surface ozone: Evidence from agricultural sector in China. *Environmental Research Letters*, *13*(3), 34019. https://doi.org/10.1088/1748-9326/aaa6d9

Zhang, Q., Zheng, Y., Tong, D., Shao, M., Wang, S., Zhang, Y., et al. (2019). Drivers of improved PM2.5 air quality in China from 2013 to 2017. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(49), 24463–24469. https://doi.org/10.1073/pnas.1907956116

Zhang, T., Yue, X., Unger, N., Feng, Z., Zheng, B., Li, T., et al. (2021). Modeling the joint impacts of ozone and aerosols on crop yields in China: An air pollution policy scenario analysis. *Atmospheric Environment*, *247*, 118216. https://doi.org/10.1016/J.ATMOSENV.2021.118216

Zhao, B., Zheng, H., Wang, S., Smith, K. R., Lu, X., Aunan, K., et al. (2018). Change in household fuels dominates the decrease in $PM_{2.5}$ exposure and premature mortality in China in 2005–2015. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(49), 12401–12406. https://doi.org/10.1073/pnas.1812955115

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(35), 9326–9331. https://doi.org/10.1073/pnas.1701762114

Zhao, C., Piao, S., Huang, Y., Wang, X., Ciais, P., Huang, M., et al. (2016). Field warming experiments shed light on the wheat yield response to temperature in China. *Nature Communications*, *7*(1), 1–8. https://doi.org/10.1038/ncomms13530

Zhao, J., Kong, X., He, K., Xu, H., & Mu, J. (2020). Assessment of the radiation effect of aerosols on maize production in China. *Science of the Total Environment*, *720*, 137567. https://doi.org/10.1016/j.scitotenv.2020.137567