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Climate effects of stringent air pollution controls mitigate future maize losses in China

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Abstract

Future anthropogenic aerosol and greenhouse gas emissions determine climate change in China, which influences crop growth and food production. However, very few studies have investigated their combined climate impacts on crop yields. Here, we apply a process-based modeling approach to examine potential climatic impacts of air pollution controls on maize yields in China for two future scenarios in the 2030s. The model suggests that reducing aerosol pollution emissions increases radiation, temperature and precipitation. Increased radiation and precipitation enhance yields while higher temperature reduces yields. These contrasting climate effects offset each other, leading to varied spatial responses in yields. Following the current legislation emission scenario, maize yield declines by 2.3% because air pollution shows only moderate reductions and the higher future temperature exerts the dominant detrimental impacts. In contrast, with the maximum technically feasible reduction scenario, the maize yield is projected to increase by 4.4% relative to the current level, because the benefit of increased radiation and precipitation outweighs the detrimental impacts of warming. Our results suggest that stringent aerosol pollution regulations can help mitigate maize yield losses in China due to the future climate warming.

Introduction

Globally, China is the one of the major regions suffering from substantial aerosol haze pollution (Cheng et al 2016). Ground-based and satellite observations reveal a widespread pollution domain (Liang et al 2016, Ma et al 2016), which occurs not only in urbanized and industrial regions (Rohde and Muller 2015) but also in many rural areas (Luo et al 2016). The overlap of aerosol pollution with the arable land raises a great concern regarding the potential adverse impacts of aerosol on agriculture and food security in China. Aerosols modulate the transparency of the atmosphere and alter the solar radiation reaching the surface (Lin et al 2015). Thus, earlier assessments of the agricultural responses to aerosol pollution often focused on the radiation-induced changes in crop photosynthesis and/or yield (Chameides et al 1999, Tie et al 2016, Zhang et al 2017). Previous estimates applying crop-radiation relationships suggest that yields are reduced by 5%–30% in eastern China due to lower radiation on heavily polluted hazy days compared to aerosol-free conditions (i.e. zero atmospheric aerosol concentration) (Chameides et al 1999, Tie et al 2016). Additionally, such a yield reduction was also confirmed by empirical models, which estimated up to 36% losses for Indian wheat (Burney and Ramathan 2014) and 10.6% for rice harvest (Auffhammer et al 2006).

Based on these results, less aerosol emission would be expected to result in a considerable yield improvements, potentially offering a solution to the detrimental
impacts of climate change on agriculture (Chameides et al 1999). Yet, the aerosol-induced radiation changes lead to concomitant changes in surface heat fluxes, temperature (Li et al 2016), and regional precipitation patterns (Jiang et al 2016). All of these aerosol climatic effects interact with plant physiological processes. Therefore, an impact assessment based on a comprehensive aerosol-climate evaluation, rather than only radiation changes, is needed.

Furthermore, the aerosol-free condition applied in previous studies (Chameides et al 1999, Tie et al 2016, Zhang et al 2017) is largely impossible to achieve because natural emissions make important contributions to the total aerosol loading and aerosol-free condition is challenging for air pollution goals. A more realistic assessment confronts specific anthropogenic aerosol emission scenarios. Simulating crop responses to emission scenarios informs the potential benefits of current and proposed air pollution regulation policies. To date, no previous study has examined aerosol-induced climate change effects on agriculture within the context of air pollution regulation, though research begins to explore impacts on ecosystem productivity (Yue et al 2017, Yue and Unger 2017).

This study aims to evaluate the responses of Chinese maize, an important commercial climate-sensitive crop (Zhang and Huang 2013), to near-future climate change, including the aerosol-induced climatic changes following possible future scenarios of air pollution. Specifically, we (1) simulate yield changes due to removal of anthropogenic aerosols in 2010s, (2) quantify the yield changes caused by greenhouse gas (GHG) emissions induced changing climate in 2030s, and (3) estimate yield responses to climate perturbations under aerosol emission scenarios in the 2030s.

Material and methods

Study regions
Maize is planted in a wide range of areas over China (figure 1) and often grown under a rainfed environment (Liu et al 2012). There are 1943 counties growing maize in China, and the county-level climate data were extracted from a historical daily climate database, which were created based on 1012 ground-based weather observational sites. These sites provide the daily climate data (including minimum and maximum temperature, sunshine hour and precipitation), and the sunshine hours were converted to radiation values using the Ångström formula (Ångström 1924). The DAYMET (daily surface weather and climatological summaries) algorithm (Thornton and Running 1999)
was then employed to interpolate these daily climate observations and derive the climate data in the 1943 counties. This historical daily climate database has been used in our several earlier studies (Zhang and Yang 2016, Zhang et al 2017)

**NASA ModelE2-YIBs model and aerosol emission scenarios**

The NASA ModelE2-YIBs model is a coupled chemistry-climate model, simulating gas-phase chemistry (NO*, HO*, O*, CO, CH4, and non-methane volatile organic compounds), aerosol (sulfate, nitrate, elemental and organic carbon, dust, and sea salt), and their interactions (Schmidt et al 2010). Both the direct and indirect radiative effects of aerosols, and absorption by multiple GHGs, are included in the radiation package of the model. Size-dependent optical properties of clouds and aerosols are computed from Mie scattering, ray tracing, and T-matrix theory, and include the effects of non-spherical particles for cirrus and dust.

Five scenarios were used in the study (table 1). The first two are for the current climate in the 2010s: (1) 2010_CAE scenario denoting the climate under the current level of aerosol emissions in the 2010s (i.e. 2006–2015); (2) 2010_NAE scenario denoting the climate with no anthropogenic aerosol emissions in the 2010s. Another three are for the future climate: (1) 2030_NAE scenario, which is the future climate without anthropogenic aerosol emissions in the 2030s (i.e. 2026–2035), (2) 2030_CLE scenario representing current legislation emission (CLE), which was adopted from the Greenhouse Gas-Air Pollution Interactions and Synergies (GAINS) integrated assessment model (Amann et al 2011) and assumed full application of national legislation for air pollution control; i.e. the 11th 5 year plan in China; by the 2030s, CO emissions are projected to decrease by 18%, SO2 by 21%, black carbon (BC) by 28%, and organic carbon (OC) by 41%, but NOx increases by 20%, ammonia by 22%, and NMVOC by 6%, compared with the 2010s emission, in China. The CLE scenario reflects a realistic target that China can achieve by the 2030s; (3) 2030_MTFR representing the maximum technically feasible reduction (MTFR) scenario adopted from Amann et al (2011), which implements all existing aerosol mitigation technologies regardless of the associated barriers and costs in China. Under this scenario, the 2030s emissions of NOx decrease by 76%, CO by 79%, SO2 by 67%, BC by 81%, OC by 89%, ammonia by 65%, and NMVOC by 62% relative to the 2010s level in China. This scenario serves as an ultimate target that the state-of-the-art aerosol mitigation technologies can potentially achieve.

The emission gap report (UNEP 2017) warned that global temperature would increase about 3.2 °C by 2100 relative to pre-industrial levels, which is close to the lower limit of warming magnitude projected by the Representative Concentration Pathways 8.5 (RCP8.5) emission scenario (van Vuuren et al 2011, Brown and Caldeira 2017). Hence, we adopt future GHG concentrations from the IPCC RCP8.5 scenario in the model.

In our previous study, we used the NASA ModelE2-YIBs model to simulate the aerosol impacts on climate (Yue et al 2017). Briefly, we applied the monthly-varying decadal average boundary conditions (sea surface temperature and sea ice distribution) of 2006–2015 for 2010s simulations and those of 2026–2035 for 2030s simulations from the IPCC RCP8.5 scenario, with CO2 increasing from 390 ppm in 2010s to 449 ppm in 2030s. Within the context of the future 2030s climate, we applied air pollution emissions from either the CLE or MTFR scenario. The NASA ModelE2-YIBs model has been extensively validated against various climate observations in our earlier work (Yue et al 2017), and, in this paper, we provide additional comparisons with other climate models in the supplemental table S1, available online at stacks.iop.org/ERL/13/124011/mmedia. Under similar model settings, the simulated impacts on climate of removing anthropogenic aerosol pollution under the current climate conditions are consistent with previous estimates (supplemental table S1).

We derive scaling matrices by dividing the climatic responses from all of the ModelE2-YIBs simulations by the values from the control simulation 2010_CAE at the grid cell level for the same month. We apply the scaling matrices to present-day observed climate to calculate the ‘perturbed’ climate either by aerosol or GHG emission changes. The derived climatic state from the different simulation experiments is then used as input to drive the maize model in offline simulations. Climate variables simulated by NASA ModelE2-YIBs model include minimum and maximum temperature, average temperature (TAVG), radiation (RAD) and precipitation (PRCP).

**APSIM-Maize model**

To simulate maize yields under above scenarios, the Agricultural Production Systems Simulator-Maize (APSIM-Maize) version 7.6 (Holzworth et al 2014)
was employed in the study. There are 11 crop stages in the APSIM-Maize, and phenology simulation is based on a bilinear model with the eight 3 hourly air temperature interpolated from the daily minimum and maximum temperatures. The model also calculates water deficit factors (WDs) for three processes (photosynthesis, phenology and leaf-expansion) each of which has a sensitivity coefficient to water stress. A WD is calculated as the ratio of actual soil water supply (potential_supply) to potential soil water demand (potential_demand) (equation (1)).

\[
WD = \max(1, \text{potential_supply}/\text{potential_demand}).
\]

The soil properties inputs (including bulk density, saturation soil water content, field capacity, wilting point, air-dry water content, soil organic matter, nitrate-nitrogen and ammonium nitrogen) required by APSIM-Maize were extracted from a gridded soil database with 10 km resolution in China (Shi et al 2002). The initial soil water contents were set to field capacity for each layer.

The APSIM-Maize model provides the sub-routines for yield sensitivity to elevated CO2 concentration in terms of transpiration efficiency and nitrogen critical concentration of leaves, but the model does not provide a set of crop parameters for the maize crop. To account for the atmospheric CO2 concentration of 449 ppm (RCP8.5) in the 2030s, transpiration efficiency in all future climate simulations was scaled by 1.047 based on the experiments of free air CO2 enrichment (Manderscheid et al 2014) and nitrogen critical concentration of leaves was scaled by 0.98 according to a chamber experiment study (Kim 2006).

The APSIM-Maize model was calibrated using phenology and yield data of 17 rainfed maize cultivars planted by the Agro-meteorological Experiment Stations (AES) in China (supplemental figure S1). For each cultivar, one set of genetic parameters was calibrated and fixed in this step. The validation shows that the ratio between observations and simulations is close to the 1:1 line and reflects a good model performance (supplemental figure S1). Additionally, we compare maize yield sensitivities estimated by our APSIM-Maize with corresponding values from previous studies that relied on statistical model (supplemental table S2). The APSIM-Maize model estimated 9.8% yield decreases with 1 °C warming, 7.7% and 3.0% yield increase as 10% higher RAD and PRCP, respectively (supplemental table S2), which generally overlapped the range reported in previous studies.

In our subsequent simulations, we run APSIM-Maize under the rainfed conditions. The sowing dates were obtained from the Chinese Agricultural Phenology Atlas (Zhang 1987) for each county, with 40 mm sowing depth and 5.7 plants m⁻² sowing density. Planting density and fertilizer applications were set for each cultivar based on the average conditions of AES to represent an actual agronomic management. The 17 sets of genetic parameters for cultivar were applied to the nearby provinces based on the locations of AES.

**Modeling and statistical analyses**

To investigate the effects of aerosol pollution-induced-climate perturbations on yields, we apply the 2010_CAE and 2010_NAE scenarios to drive the APSIM-Maize model. The percentage changes in yield under the 2010_CAE scenario relative to 2010_NAE represent the aerosol-induced climate change impacts on yields due to present-day anthropogenic aerosol emissions.

To simulate the effects of GHG-induced climate change on yields, we simulate maize yields under the 2030_NAE and 2010_NAE scenarios. The associated yield changes indicate the magnitude of yields due to the changing climate induced by GHG emissions exclusively. In this comparison, we fixed CO2 concentrations at the 2010s level because this part of analysis is to compare the effects of GHG-induced climate impacts and aerosol-induced climate impacts on maize without CO2 fertilization.

To quantify the overall effects of climate associated with GHG emissions and future anthropogenic aerosol pollution in the 2030s, we use the 2030_CLE and 2030_MTFR scenarios to drive the APSIM-Maize model. The resultant yield change relative to 2010_CAE indicates the combined effects of future GHG and aerosol pollution on maize yields. In addition, we perform factorial experiments to isolate the roles of individual climate variables on yields by allowing one climate variable only to follow the 2030_CLE or 2030_MTFR scenario but hold other variables fixed to 2010_CAE values and drive the APSIM-Maize model with this newly constructed factorial experiment. In this comparison, we execute both model projections with and without CO2 fertilization effect under 2030_CLE and 2030_MTFR scenarios. The area-weighted means are calculated for each region (figure 1), and the statistical differences between scenarios are calculated based on paired t-test with $p < 0.05$ as statistical significance.

**Results**

**Effects of aerosol and GHG emissions on climate and yields**

Current anthropogenic aerosol emissions in the 2010s reduce RAD by 13% in China over the maize growing season (figure 2(a); table 2). The decreases in RAD are particularly obvious in the northeast, north and east, with 11.4%, 17.1% and 15.6% reductions (table 2), respectively, compared with the 2010_NAE scenario. Other regions also exhibit declines in RAD (figure 2(a)) but to a less extent (7.5% to 10.7%)(table 2). Anthropogenic aerosols also result in a widespread cooling (figure 2(c)), with TAVG reductions of 0.8 °C on average (table 2). Anthropogenic aerosols cause
different impacts on PRCP across China (figure 2(e)) although most regions show a decrease trend. PRCP is predicted to decrease by 10.5% in the northeast, 14.0% in the north, 8.8% in the northwest, 4.3% in the east, and 2.9% in central (table 2), while PRCP increases by 3.5% in the southwest and 4.8% in the south (table 2).

Without anthropogenic aerosols, GHG emissions cause a higher TAVG in the 2030s (figure 2(d)) with a range from 0.3 °C to 0.9 °C (table 2). However, changes in RAD are only 1.2% (p > 0.05) with both positive and negative values from −1.9% to 2.9% (table 2). For PRCP, GHG emissions result in lower values in the north (−3.2%), northwest (−8.4%) and east (−15%) while higher values in other regions (0.9%–5.3%) (table 2). These positive and negative changes offset each other, leading to a minor change (0.2%) in average PRCP over China (table 2).

Generally, both anthropogenic aerosols and GHG-induced changing climate exert a detrimental influence on maize yields in China (figure 3). Aerosol
pollution climate effects in the 2010s reduce yields by 4.8% ($p < 0.05$, table 2), with the largest reduction of 14.0% in the north region (figure 3(a); table 2). Future GHG emissions reduce yield by 2.4% in the 2030s with the largest changes in northwest (figure 3(b); table 2). The northeast is the exception for both effects of anthropogenic aerosols and GHG emissions. An increase in yields was simulated due to anthropogenic aerosols in the 2010s (3.4%, $p < 0.05$) and GHG emissions in the 2030s (0.9%, $p > 0.05$) in the region.

Changes in maize yields due to future aerosol pollution

Compared to 2010_CAE, simulated RAD in the 2030_CLE scenario shows a significant increase of 2.0% in China (figure 4(a); table 3). The TAVG of all counties increases on average by 0.9 °C under the 2030_CLE scenario (figure 4(c)), with a regional range from 0.2 °C–1.1 °C relative to the scenario 2010_CAE (table 3). In contrast to the uniform warming, a mixed PRCP change is simulated region by region (figure 4(e)). Generally, PRCP increases in most regions, with 16.1% in the north, 10.3% in the northwest, 4.9% in the east, 4.4% in central and 3.6% in the south (table 3), except for reductions of 1.9% in the southwest (table 3).

Predicted climatic changes in the 2030_MTFR scenario resemble those in the 2030_CLE except for stronger magnitudes (figures 4(b), (d), (f)). For example, simulated RAD substantially increases by 8.3% (table 3), around four times higher than the value of 2.0% in 2030_CLE. Slightly larger warming trends are

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Table 2. Simulated percentage changes in mean growing season climate variables (RAD, TAVG, PRCP) in the 2010_CAE and 2030_NAE scenarios, and associated changes in yields, compared with the 2010_NAE scenario. The number with bold font indicates statistical significance.

| Scenario       | Regions   | RAD  | TAVG °C | PRCP % | Yield % |
|----------------|-----------|------|---------|--------|---------|
| 2010_CAE versus Northeast | −11.4 | −0.9 | −10.5 | 3.4    |
| 2010_NAE North  | −17.1 | −0.9 | −14.0 | −14.0 |
| 2010_NAE Northwest | −7.5  | −0.4 | −8.8  | −4.2   |
| 2010_NAE East   | −15.6 | −0.8 | −4.3  | −9.5   |
| 2010_NAE Central | −10.2 | −0.4 | −2.9  | −3.1   |
| 2010_NAE Southwest | −8.4  | −0.5 | −3.5  | −1.7   |
| 2010_NAE South  | −10.7 | −0.4 | −4.8  | −4.2   |
| 2010_NAE China  | −13.0 | −0.8 | −8.7  | −4.8   |
| 2030_NAE 2010_NAE | Northeast | 0.9  | 0.9    | 5.3    | 0.9     |
| 2010_NAE North  | 1.8    | 0.8  | −3.2   | −3.7   |
| 2010_NAE Northwest | 2.4   | 0.9  | −8.4  | −10.6  |
| 2010_NAE East   | 2.9    | 0.8  | −15.0  | −6.5   |
| 2010_NAE Central | −0.6   | 0.3  | 3.6   | −1.8   |
| 2010_NAE Southwest | −0.7  | 0.3  | 3.6   | −4.1   |
| 2010_NAE South  | −1.9   | 0.3  | 0.9   | −3.4   |
| 2010_NAE China  | 1.2    | 0.8  | 0.2   | −2.4   |
predicted, with an overall 1.0 °C increase in China (table 3). In addition, more areas show increasing PRCP in 2030_MTFR compared to 2030_CLE (figure 4(f)). On average, aerosol pollution reductions in the 2030_MTFR scenario result in an increase of 9.4% in PRCP as shown in table 3.

Despite the elevated CO2 concentration, maize yields are projected to decline by 2.3% in 2030_CLE on the national level (table 3; figure 5(a)). Regionally, even though yields increase by 15% in northwest and 1.7% in the north, there is a range of 2.8%–6.8% yield decline in 2030_CLE in other regions (table 3). In contrast, yield reduction in 2030_MTFR is only simulated in some counties located in the northeast and southwest (figure 5(b)). Meanwhile, yield substantially increases in the north (10.7%), northwest (11.1%) and
east (5.8%) (table 3). On the national level, maize yield is predicted to increase by 4.4% in 2030_MTFR compared to the 2010_CAE level (table 3).

Role of individual climate variables on yields
We isolate the impacts of individual future climate variables on maize yields (table 4). Warming reduces yields with a similar magnitude under the two future scenarios, to the extent of 7.2% in 2030_CLE and 8.0% in 2030_MTFR. PRCP change effects are most dominant in the northwest and north (table 4). RAD increases are beneficial for maize yields in general. Yield enhancement by RAD in 2030_MTFR is higher (7.7%) than that in 2030_CLE (1.4%) (table 4). The interaction effects of above climate variables were also calculated by the difference between the additive yield changes by above individual climate variable and the combined climate effects in table 3. We found a very few interaction effect (between −0.6% and 0.6%) except the eastern region (−3.5%) in the 2030_MTFR scenario (table 4).

Discussion
Aerosol pollution effects on climate and maize yields
Anthropogenic aerosols reduce RAD during the maize growing season (figure 2(a)) because the light extinction of fine particles prevents solar radiation from reaching earth surface (Lin et al 2015), consequently cooling down TAVG (figure 2(c)). In addition,
aerosols generally reduce PRCP with regional variations (figure 2(e)). As a result, anthropogenic aerosols cause yield reductions of 4.8% due to the combined perturbations in RAD, TAVG, and PRCP. This impact can be explained by considerable reductions in simulated RAD and PRCP, which decrease plant photosynthesis (Wijewardana et al. 2016) and aggravate the water stresses of maize (Zhang 2004). These two negative effects outweigh the benefits from the lower TAVG. The northeast is an exception where there is a considerable reduction in RAD that does not influence yields (table 2). This result is consistent with our former study for rice (Zhang et al. 2017), reflecting a light saturation process. Our impact estimate (4.8%) for anthropogenic aerosols is lower than the values of 5%–30% in earlier assessments (Chameides et al. 1999, Tie et al. 2016), because we consider the combined radiative and associated other climatic effects of aerosols, which show offsetting impacts on maize yields. This finding emphasizes the importance of aerosol-induced temperature and precipitation changes in addition to radiative perturbations in the assessment of air pollution effects on agriculture.

Our evaluation of the warming climatic impacts of GHG emissions is in good agreement with other similar studies (Liu et al. 2012, Ju et al. 2013). Our model predicts that around 2.4% of the yields are lost due to the GHG-induced changes in climate (table 2). This yield loss could be further exacerbated because warming is accompanied with intensified drought stress in north and northwest (table 2). In comparison, yield loss due to the climatic impacts of anthropogenic aerosols in 2010s (−4.8%) is twice that from GHG effects (−2.4%) in 2030s over China. Therefore, anticipated future yield losses due to GHG climate warming may be mitigated by reducing aerosol pollution.

We further quantified the yield changes under two future aerosol emission scenarios (2030_CLE and 2030_MTFR). For these two scenarios, the magnitude of warming (0.9 °C in 2030_CLE and 1.0 °C in 2030_MTFR) is slightly higher than the results only considering GHG effects (0.8 °C in 2030_NAE) due to the additional warming by reducing aerosols. The higher TAVG shows a consistent and negative impact on yields (table 4). In contrast, the aerosol-induced changes in PRCP and RAD have both positive effects on yields (table 4), which offset yield losses caused by warming. Under both scenarios, larger PRCP results in higher yields in the north and the northwest, regions with arid climatology (Zhang and Huang 2013), and imposes an overall positive effect (table 4). Due to much lower aerosol emissions, the 2030_MTFR scenario exhibits substantially higher RAD (8.3%) than 2030_CLE (2.0%). The differing RAD changes is the dominant reason that yields increase by 4.4% in 2030_MTFR but decrease by 2.3% in 2030_CLE, because the light enrichment offsets the negative impact of warming in the former scenario.

**Implications for future air pollution control in China**

The projected yield shows opposite sign changes in the 2030_CLE and 2030_MTFR scenarios, indicating the critically important role of aerosol pollution regulation in the mitigation of climate change impacts on maize. This result has important implications for the future air pollution emission controls in China. More stringent air pollution emission reductions through full implementation of all available control technologies (i.e. 2030_MTFR scenario) has the potential to enhance yields because the positive effects of RAD and PRCP can outweigh the negative impact of TAVG.

| Scenario      | Region     | Yield_RAD % | Yield_TAVG % | Yield_PRCP % | Yield_INTER % |
|---------------|------------|-------------|--------------|--------------|--------------|
| 2030_CLE versus 2010_CAE | Northeast | 0.3 | −8.7 | 1.4 | 0.1 |
| | North | 3.6 | −6.9 | 4.4 | −0.2 |
| | Northwest | 0.6 | 0.3 | 12.2 | −0.3 |
| | East | 3.8 | −7.6 | −0.2 | −0.6 |
| | Central | −1.4 | −4.3 | 0.5 | −0.1 |
| | Southwest | 0.0 | −6.9 | −0.3 | −0.1 |
| | South | −1.0 | −3.1 | 0.9 | −0.2 |
| | China | 1.4 | −7.2 | 2.6 | −0.1 |
| 2030_MTFR versus 2010_CAE | Northeast | 2.4 | −8.2 | 4.7 | 0.3 |
| | North | 15.2 | −9.0 | 3.3 | 0.1 |
| | Northwest | 2.3 | −5.2 | 11.1 | 0.6 |
| | East | 18.6 | −9.6 | −0.9 | −3.5 |
| | Central | 6.2 | −5.6 | 0.2 | −0.1 |
| | Southwest | 5.0 | −6.8 | −0.7 | 0.0 |
| | South | 4.9 | −3.2 | 1.5 | −0.2 |
| | China | 7.7 | −8.0 | 3.4 | 0.1 |
These results suggest that significant air pollution emission reductions can help alleviating expected maize yield loss due to climate warming in the near future. A systematic assessment is urgent to address the sectoral mitigation technology options for the future air pollution control plans and actions in China.

**Uncertainties of diffuse fraction**

Our earlier investigation studying Chinese rice (Zhang et al 2017) has found the decreased diffuse fraction (the ratio of diffuse radiation from the total solar radiation, DF) as lower aerosol concentration may pose a negative effect on rice radiation use efficiency (RUE), even though such effect is only happened in the northeast region when atmospheric aerosol concentrations were reduced by at least 80%. However, several factors make it difficult in our current study to simulate the effects of DF on maize; (1) APSIM-Maize does not distinguish effects of diffuse radiation (Holzworth et al 2014); (2) diffuse radiation was not measured in most ground-based weather sites, and the daily DF data is therefore missing.

Despite those uncertainties, changes in DF in our aerosol emission scenarios are considered to pose a limited impact on maize (figure 6). The reason is that increases in RUE of maize were only greatest for increases in diffuse radiation when the DF was less than 0.3; i.e. RUE was increased by 12.6% per each 0.1 unit increase in DF over the range of 0.15 to 0.3 fraction of diffuse radiation (Sinclair et al 1992). Beyond the point, the RUE increases tend to level off; there is only 2.6% RUE increase per 0.1 unit DF over the range of 0.3−0.5 (Sinclair et al 1992). In our study, based on the MERRA-2 monthly data product (Gelaro et al 2017),

![Figure 6](image_url)
DF is greater than 0.3 over the maize growing season months in 98.8% counties during the period of 2006–2015 (figure 6(a)), and decreases in diffuse fraction in 2030_CLE (almost no change) and 2030_MTFR (0.04 decrease on average) are also very few (figure 6(b)). These results indicate that RUE differences resulting from varying diffuse radiation may be sufficiently small when compared with other factors that the fraction of diffuse radiation may not be the major climatic driver in simulating aerosol influences on maize in China. Certainly, future work still needs to incorporate an updated model and daily diffuse radiation data to quantitatively simulate varying RUE and associated yield changes induced by lower DF.

Conclusions

This study presents the first assessment to evaluate potential climate impacts on maize yields in the 2030s, as driven by CLE and MTFR aerosol emission scenarios. Under the two scenarios, we simulated changes in RAD, TAVG, and PRCP due to reduced aerosols, and quantified the consequent impacts on maize yields. We investigate the combined effects of RAD, TAVG and PRCP impacts of aerosols on crop yields, while the earlier assessments only focus on changes in RAD (Chameides et al. 1999, Tie et al. 2016, Zhang et al. 2017). We found that aerosol pollution reductions cause higher TAVG and PRCP, in addition to RAD. Higher PRCP and RAD improve yields but warmer TAVG declines yields. Based on our model, maize yield declines by 2.3% with the CLE policies, as driven by CLE and MTFR aerosol emission scenarios. Under the two scenarios, we simulated as driven by CLE and MTFR aerosol emission.

An important remaining question is whether the decrease in the DF is a significant climatic driver or not, as lower aerosol emissions. For maize, the DF may be not a major consideration because the DF is often not, as lower aerosol emissions. For maize, the DF may be not a major consideration because the DF is often not, as lower aerosol emissions. For maize, the DF may be not a major consideration because the DF is often not, as lower aerosol emissions. For maize, the DF may be not a major consideration because the DF is often not, as lower aerosol emissions.

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