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Key Points:

- Over the twentieth century, the global maize and soybean yields driven by environmental and management factors increase
- Projected future [CO_2] increase has a positive effect, and warmer climate has a negative effect on soybean yield by the 2090s
- Projected maize yield is increased by 20% under RCP4.5-SSP2 but is decreased by 14% under RCP8.5-SSP5 by the end of the 21st century

Supporting Information:

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

Correspondence to:

A. K. Jain,
jain1@illinois.edu

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Author Contributions:

Conceptualization: Tzu-Shun Lin, Atul K. Jain
Data curation: Tzu-Shun Lin, Yang Song, Peter Lawrence, Atul K. Jain
Formal analysis: Tzu-Shun Lin, Atul K. Jain
Funding acquisition: Atul K. Jain
Investigation: Tzu-Shun Lin, Yang Song, Atul K. Jain

Worldwide Maize and Soybean Yield Response to Environmental and Management Factors Over the 20th and 21st Centuries

Tzu-Shun Lin[1], Yang Song[2], Peter Lawrence[3], Haroon S. Kheshgi[4], and Atul K. Jain[1]

[1]Department of Atmospheric Sciences, University of Illinois, Urbana, IL, USA, [2]Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ, USA, [3]National Center for Atmospheric Research, Boulder, CO, USA, [4]ExxonMobil Research and Engineering Company, Annandale, NJ, USA

Abstract A land process model, Integrated Science Assessment Model, is extended to simulate contemporary soybean and maize crop yields accurately and changes in yields over the period 1901–2100 driven by environmental factors (atmospheric CO_2 level ([CO_2]) and climate), and management factors (nitrogen input and irrigation). Over the twentieth century, each factor contributes to global yield increase; increasing nitrogen fertilization rates is the strongest driver for maize, and increasing [CO_2] is the strongest for soybean. Over the 21st century, crop yields are projected under two future scenarios, RCP4.5-SSP2 and RCP8.5-SSP5; the warmer temperature drives yields lower, while rising [CO_2] drives yields higher. The adverse warmer temperature effect of maize and soybean is offset by other drivers, particularly the increase in [CO_2], and resultant changes in the phenological events due to climate change, particularly planting dates and harvesting times, by 2090s under both scenarios. Global yield for maize increases under RCP4.5-SSP2, which experiences continued growth in [CO_2] and higher nitrogen input rates. For soybean, yield increases at a similar rate. However, in RCP8.5-SSP5, maize yield declines because of greater climate warming, extreme heat stress conditions, and weaker nitrogen fertilization than RCP4.5-SSP2, particularly in tropical and subtropical regions, suggesting that application of advanced technologies, and stronger management practices, in addition to climate change mitigation, may be needed to intensify crop production over this century. The model also projects spatial variations in yields; notably, the higher temperatures in tropical and subtropical regions limit photosynthesis rates and reduce light interception, resulting in lower yields, particularly for soybean under RCP8.5-SSP5.

Plain Language Summary A land surface model is used to estimate changes in global maize and soybean yields in response to changes in environmental conditions (climate (temperature and precipitation) and carbon dioxide concentration ([CO_2])), and agricultural management activities (irrigation, nitrogen application, and dynamic planting time decisions) over the 20th and 21st centuries. Estimated current crop yields compare well with the observed crop yields circa 2000. We then project how maize and soybean resources may change in the future under two climate and socio-economic assumptions: a high-end emission pathway (RCP8.5-SSP5) and a mitigated emission pathway (RCP4.5-SSP2). We find that future increase in [CO_2] drives yield higher and alleviates the negative climate impacts on soybean productivity. The maize yield increases under the mitigated emission pathway because of earlier planting dates and the continued [CO_2] growth and nitrogen application. However, under the high-end emission pathway with greater warming and lower nitrogen application, the maize yield reduces by 14% by the end of this century, suggesting that climate change mitigation and improved agricultural technologies and practices may be needed to intensify crop production over this century. Crops' exposure to heat stress during grain formation is represented by canopy temperature and is projected to increase by the 2090s.

1. Introduction

Crop yield has and will be affected by environmental factors, such as atmospheric carbon dioxide level ([CO_2]) and changes in temperature and precipitation patterns. For instance, an increase in the [CO_2] positively influences the crop yields due to an increase in the photosynthesis process and reduced water requirement under increasing [CO_2] (Ainsworth, 2008; Gray et al., 2016). On the other hand, increasing

Methodology: Tzu-Shun Lin, Yang Song, Peter Lawrence, Haroon S. Kheshgi, Atul K. Jain
Project Administration: Atul K. Jain
Software: Tzu-Shun Lin
Supervision: Atul K. Jain
Validation: Tzu-Shun Lin, Yang Song, Atul K. Jain
Visualization: Tzu-Shun Lin, Peter Lawrence, Haroon S. Kheshgi
Writing – original draft: Tzu-Shun Lin, Atul K. Jain
Writing – review & editing: Tzu-Shun Lin, Yang Song, Peter Lawrence, Haroon S. Kheshgi, Atul K. Jain

temperature increases atmospheric water demand, causing water stress and drought that severely decrease crop growth and yields worldwide (Lobell et al., 2014; Rahimi-Moghaddam et al., 2018). The Global Gridded Crop Model Intercomparison (GGCMI) of Agricultural Model Intercomparison and Improvement Project (AgMIP) compares the crop yield results for global gridded crop models over this century for maize, wheat, rice, and soybean (Elliott et al., 2015; Müller et al., 2017). The AgMIP study generally finds that the models' estimated effects of environmental factors on crop yields are qualitatively consistent with the measurement studies (Müller et al., 2015).

However, the magnitude of these effects remains uncertain on a global scale and understanding of environmental factors' interactions with crop management practices (e.g., irrigation and nitrogen (N) fertilizer inputs), and the effects of extreme climate events, such as heat stress (HS) and droughts on yields, remain incomplete. Studies show that agricultural management practices generally can alleviate not only the adverse effects of climate change but also modulate the positive effects of increasing [CO2]. Levis et al. (2018) find irrigation can mitigate the yield losses due to increased respiration and water demand caused by temperature increases. Similarly, Rosenzweig et al. (2014) simulate higher yields under the assumption of no N-limitation. However, the AgMIP study does not explicitly study the synergistic effects of environmental and management factors and the effects of extreme climate events, specifically the effects of HS on crop productivity.

Studies show interactions between effects of environmental and management factors on crop yield. For instance, crop growth enhanced by the CO_2 fertilization effect is suppressed by low N supply and water stress conditions during the growing season (Ainsworth, 2008; Jain et al., 2009). Simultaneously, as the climate becomes warmer and wetter, inorganic soil N availability increases due to enhanced N mineralization associated with increased microbial decomposition and respiration rates (Jain et al., 2009; Rustad et al., 2001). Thus, improved N availability and uptake lead to enhanced crop productivity. Conversely, N deficits reduce crop growth rate, biomass, harvest index, and yields (Pandey et al., 2000). Although some crops are N fixation crops, for example, soybean field measurements suggest N fertilization can somewhat enhance yield depending on the yield potential of abiotic and biotic stresses (Cafaro La Menza et al., 2017; Salvagiotti et al., 2008).

Extreme climate events such as HS shorten both the vegetative and reproductive phases of the crop phenology (Asseng et al., 2004; Teixeira et al., 2013), resulting in the decrease of the average growing season length and crop yields. In addition, crops are sensitive to critical high temperatures during the reproductive period (Bolanos & Edmeades, 1996; Deryng et al., 2014; Gourdji et al., 2013). During this period, the negative impact of high temperature reduces carbon assimilation at the leaf level and directly impairs flower and crop grain development, resulting in crop yield loss (Sage et al., 2015; Teixeira et al., 2013).

This study aims to address three specific questions: (a) what are the synergistic effects of environmental ([CO_2] and climate) and management (irrigation and nitrogen input) factors on maize (a C4 crop) and soybean (a C3 crop) yields over the past century? (b) what are the effects of extreme HS on maize and soybean yields over the past century? (c) how do these effects change under two future scenarios over the 21st century?

It is to be noted that while several modeling studies have evaluated the effects of environmental factors, such as climate change, on crop yields at the site, country, and/or global scale, this is the first study, which quantifies not only the synergistic effects of climate change and management factors but also extreme climate events on crop yields over the past and 21st centuries. In addition, while few previous modeling studies have quantified the effects of HS, either at a regional or global scale, they use prescribed surface air temperature data to calculate the HS effect. In contrast, this is the first study that estimates the HS effect using the canopy temperature on a global scale because the canopy temperature explains better yield reductions associated with heat stress under drier, rainfed, and irrigated conditions.

We address the above three questions using a process-based land surface model, the Integrated Science Assessment Model (ISAM) (Song et al., 2013). The model is driven by historical climate data (1901–2015) and projected climate data (2016–2100) for two Representative Concentration Pathways: RCP4.5 and RCP8.5. The other model input variable–N input is developed here using the literature data for the historical time and two Shared Socioeconomic Pathways, SSP2 and SSP5, which represent agricultural activities under

RCP4.5 and RCP8.5 scenarios, respectively (O'Neill et al., 2014; van Vuuren et al., 2011). We also evaluate our model results for crop yield at regional (Figure S1 in Supporting Information S1) and global scale by comparing data and other published model studies for the historical and future periods.

2. Methods and Input Data

2.1. Model Description

ISAM, improved upon and used in this study, is a coupled biogeochemical and biogeophysical model with 0.5° × 0.5° spatial resolution and multiple temporal resolutions ranging from half-hour to yearly time steps. It simulates C, N, energy, and water budgets for various terrestrial ecosystems through photosynthesis, surface hydrology, radiative transfer, carbon allocation, and ecosystem respiration (Barman et al., 2014a, 2014b; Yang et al., 2009). Moreover, ISAM incorporates crop growth processes for C3 and C4 food crops (maize, soybean, wheat, and rice) and bioenergy grasses (miscanthus, cave-in-rock, and alamo), which are evaluated at site-level, regional, and global scales (Gahlot et al., 2020; Lin et al., 2017; Niyogi et al., 2015; Song et al., 2013, 2015, 2016). Some of the important features, unique to ISAM and critical for crop yield calculations, include (a) dynamic crop-specific phenology and carbon allocation schemes (Song et al., 2013, 2015), accounting for the sensitivity of different crops to extreme environmental conditions; (b) dynamic vegetation structures, which better capture seasonal variability in leaf area index (LAI), canopy height, and root depth; (c) dynamic root distribution processes at the depth that improve simulated root-mediated soil water uptake and transpiration. The current study considers two crops: maize and soybean.

ISAM has been extensively calibrated, validated, and evaluated for agricultural applications (Gahlot et al., 2020; Niyogi et al., 2015; Song et al., 2013, 2015, 2016) and in nonagricultural application studies (Barman et al., 2014a, 2014b, 2016; El-Masri et al., 2013, 2015; Gahlot et al., 2017; Jain et al., 2006, 2013). Specifically, modeled estimated LAI, above and below-ground biomass, yield, and carbon, water, and energy fluxes for maize and soybean are calibrated and evaluated using the site level and county scale observation data (Song et al., 2013; Niyogi et al., 2015).

To improve the ISAM simulated crop growth processes and yields at a global scale, we extend ISAM to include (a) crop-specific dynamic planting time decision (Text S1 in Supporting Information S1), (b) crop-specific seeding rates (Text S2 in Supporting Information S1), (c) the curvature to the light response curve for the CO_2 fertilization effect (Text S3 in Supporting Information S1), (d) nutrient (i.e., N) stress while allocating the assimilated carbon to leaf, root, stem, and grain pools (Text S4 in Supporting Information S1), and (e) extreme heat stress effect during the crop reproductive stage of penology (Text S5 in Supporting Information S1). After implementation of newly added processes, modeled yields for the two crops are further evaluated for elevated [CO_2], heat stress effect, N input, and irrigation effects using Free-Air Carbon dioxide Enrichment (FACE) experiments and other site-specific data sets, and published model results at specific sites, regional, and global scales over historical time and under future scenarios.

2.2. Input Data

2.2.1. Environment Forcing Data

Atmospheric CO_2 concentrations and climate conditions for historical (1901–2015) and future (2016–2100) periods are inputs for ISAM simulations of crop productivity. For the historical period, we use yearly [CO_2] data from the Global Carbon Budget (Quéré et al., 2018) and climate forcing data from Climate Research Unit–National Centers for Environment Prediction (CRU-NCEP, Harris et al., 2014; Viovy, 2016), which are available at a 6-hr time scale. The future crop productivity calculations are performed for two climate scenarios: RCP 4.5-SSP2 and RCP8.5-SSP5 (O'Neill et al., 2014; van Vuuren et al., 2011). RCP4.5-SSP2 (hereafter referred to as RCP4.5) is a scenario to stabilize the total radiative forcing to 4.5 W/m^2 by 2100. In RCP4.5, economic, societal, and technological trends are assumed to be similar to historical patterns.

RCP8.5-SSP5 (hereafter referred to as RCP8.5) is a high energy demand and relatively rapid economic development scenario, causing high emissions and increased greenhouse gas (GHG) concentration by 2100. This scenario represents the highest GHG emission scenario available in the literature, leading to total radiative forcing to 8.5 W/m^2 by 2100. ISAM simulations for the two scenarios use [CO_2] data from Meinshausen et al. (2011) and climate forcing data from a single ensemble member of NCAR's Community Earth System Model (CESM) results (Levis et al., 2018; Ren et al., 2018). The CESM model results are bias-corrected using the CRU-NCEP climate data as described in Text S6 in Supporting Information S1. It is to note that the future input data, such as climate input data, is one primary but the inevitable source of uncertainty in modeling studies (Barman et al., 2014a, 2014b; Kheshgi et al., 1999; Jagtap & Jones, 2002). CESM climate scenarios that provide diurnal cycles of climate data allow us to assess the heat stress impact on maize and soybean yields at the hourly scale, which other global climate model outputs do not provide.

2.2.2. Crop Specific Area

The cropland area varies for the historical model simulations from 1901 to 2015. Thereafter, the area under the future scenarios remains fixed at an average of 1996–2005 conditions (Figure S2 in Supporting Information S1). The time-varying crop-specific annual area for the historical period is generated at 0.5° x 0.5° from a combination of global crop-specific harvested areas circa year 2000 (M3, Monfreda et al., 2008) and the Land-Use Harmonization 2 data sets for the period 1901–2015 (LUH2, Hurtt et al., 2020). The process for calculating crop-specific areas at a 0.5×0.5 spatial scale is described in Text S7 in Supporting Information S1. Between 1901 and 2015, the maize area increased from 88 to 167 million ha, whereas the soybean area increased from 45 to 86 million ha (Figure S2 in Supporting Information S1). The spatial distribution of croplands for 1996–2005 shows the higher areas for both crops in midwest North America (NA), Europe (EU), South America (SA), South and Southeast Asia (SSEA), and the northeastern plain of China (CHN) (Figure S3 in Supporting Information S1).

2.2.3. Crop Specific N Input Amount

Crop-specific annual spatial distribution of N input (fertilizer, manure, and atmospheric deposition) rates (kg N/ha) are estimated for historical time and the two future scenarios using the method described in Text S8 in Supporting Information S1. We use the LUH2 data set for N fertilizer (Hurtt et al., 2020), Lamarque et al. (2011), and Tian et al. (2018) data for airborne nitrogen deposition (wet + dry), M3 total N input (sum of fertilizer, manure, and deposition) data for maize and soybean (Mueller et al., 2012), and manure data from Zhang et al. (2017).

The estimated global N fertilizer for maize over the period 1961–2010 was 509 Tg, which was consistent with the other studies' estimated value of 517 TgN (Ladha et al., 2016). In the year 2000, the total N input rate for maize and soybean were 108 kgN/ha and 59 kgN/ha (Figure S4a in Supporting Information S1). Of these totals, 77% and 64% of N are attributed to N fertilizer for maize and soybean. N manure contributes 15% for maize and 19% for soybean. Higher consumption appears in higher production regions, including CHN, NA, and EU (Figure S5 in Supporting Information S1). By the 2090s, N input rates for maize are about 200 kgN/ha under RCP4.5 and 107 kgN/ha under RCP8.5; and they are about 88 kgN/ha under RCP4.5 and 59 kgN/ha under RCP8.5 for soybean (Figure S4a in Supporting Information S1). N consumption is especially increased in AF and SA under RCP4.5 (Figure S5 in Supporting Information S1). The N input rates for soybean were almost 50% less than those of maize because it is an N-fixing crop. Some crop modeling studies assume that neither N fertilizer nor N stress is applied to soybean (Iizumi et al., 2017). In contrast, we follow field-based studies, which show N fertilizer is applied to soybean crops to prevent N deficiency (Salvagiotti et al., 2008) and include N fertilizer and N stress to estimate soybean productivity.

The global N fertilizer rates increase for both crops over historical time (Figure S4b in Supporting Information S1). The global average N fertilizer application rates are higher under RCP4.5 (Figure S4b in Supporting Information S1) for future scenarios due to lower N use efficiency (Popp et al., 2017) and follow the historical trend. In contrast, rates decrease under RCP8.5 due to an increase in soil nitrogen uptake efficiency due to technological change (Popp et al., 2017).

The total manure N rates increased from 7.5 (maize) and 5.5 (soybean) kgN/ha in 1901 to 16.5 (maize) and 11.0 (soybean) kgN/ha in 2000 (Figure S4c in Supporting Information S1). Of these total, about 35% is assumed organic N and 65% is assumed inorganic (ammonium) N (Dangal et al., 2019). Manure application rate is increasing for maize but more in RCP4.5 than in RCP8.5 (Figure S4c in Supporting Information S1). The manure application rate for soybean also increases under both scenarios, but at a slower rate than maize and the rate of increase is similar in both scenarios.

Historical N deposition rate had been increased since 1940, and there was a near peak around 1990 followed by a decrease until 2015 (Figure S4d in Supporting Information S1). Future N deposition rates follow the fossil-fuel combustion patterns and increase under RCP8.5 but decrease under RCP4.5.

In ISAM, the N fertilizer, which is inorganic N, is added to the soil mineral N pools based on $NH4^+/NO3^-$ (Nishina et al., 2017) after emergence. The N fertilizer is evenly distributed for the first four weeks after emergence. The inorganic and organic manure N applications follow the same timing as N fertilizer, but the organic manure N is added to the soil, which is decomposed to mineral N gradually, and the inorganic N is added to the soil N mineral pool. N deposition has two components NHx and NOy, which are added to soil $NH4^+$ and NO_3^- pools at a weekly interval.

2.2.4. Irrigation

The cropland area of each grid cell is divided into irrigated and rainfed areas. The irrigated fractional area for each grid cell for 1901–2015 is assigned based on LUH2 (Hurtt et al., 2020) (Text S7 in Supporting Information S1). After that, the irrigated area in each grid cell under the future scenarios remains fixed at the 1996–2005 level. ISAM provides water on an irrigated fraction of land when the root-zone soil water is limiting for crop photosynthesis, but the crop LAI is greater than zero as described in Text S9 in Supporting Information S1.

Irrigation fraction continuously increased in the twentieth century but is less than 20% of individual crop areas (Figure S6a in Supporting Information S1). Regarding irrigation water amount, ISAM estimates approximately 34 and 16 km^3 in the year 2000, due to growing maize and soybean on irrigated croplands, which fall within global gridded crop models' (11 models for maize and 10 models for soybean) estimated range values (11–237 for maize and 3–36 for soybean) (AgMIP, Müller et al., 2019) (Figure S6b in Supporting Information S1).

2.3. Historical Yield Date For Model Evaluation

To evaluate the model estimated yields with the data available in the literature (Section 3.1), we use three global gridded data sets: GDHY (Iizumi et al., 2014), M3 (Monfreda et al., 2008), and SPAM (You et al., 2014); and one country scale data set: FAOstat (FAOstat, 2017). These data sets provide yield for different periods, GDHY for 1982–2006, M3 for ca. 2000 (mean for 1997–2003), SPAM for 2000 and 2005, and FAOstat for 1961–2018. We selected a 10-year period, 1996–2005, to compare the model results with the literature data. There are a total of 23 values available from the literature data over this period, one (2000) from M3, ten (1996–2005) each from GDHY and FAOstat, and two (2000 and 2005) from SPAM. We then select 23 model simulated values, which correspond to the same years. We calculate mean and median values from modeled and literature data values, which we compare in Section 3.1.

2.4. Experimental Design and Analysis

ISAM is spun-up by repeating the hourly climate forcing data (Harris et al., 2014; Viovy, 2016) for the period 1901–1920, and fixed the year 1900 values for $[CO_2]$ (296.8 ppm, Le Quéré et al., 2018), crop area, and N input (Section 2.2). The model is run until the soil temperature, moisture, and C and N pools reach a steady state. The spin-up process is described in detail in El Masri et al. (2015) and Song et al. (2016). The spin-up simulation follows transient model simulations with prescribed spatial and temporal forcing data for climate, N input, and $[CO_2]$ for 1901–2100. The model calculates the annual yields and corresponding C, N, water, and energy fluxes. Here, simulated crop yields are converted from modeled dry grain carbon with the assumption of 45% carbon in the dry matter (Lobell et al., 2002) and average water content of 12% for maize and 9% for soybean (Wirsenius, 2000).

We also generate three sets of simulations: one to examine crop productivity over the period 1901–2005, and the other two for the two scenarios over the period 2006–2100. Each set consists of four model experiments (E_{CO2}, E_{Cli}, E_{Nit}, and E_{Irr}) to examine each factors' effects, and one additional experiment to study the total effect of management (E_{Man}) over the two time periods (Table 1). In the reference case (E_{Ref}), all four factors vary with time over two time periods. The five additional simulations are performed differently for the periods 1901–2005 and 2006–2100. For the 1901–2005 set, one of the four factors remains fixed at the 1900

Table 1
Model Experiment Design to Study the Effects of Individual Environmental and Management Factors Over 1901–2100

Cases	[CO_2]	Climate	N Input	Irrigation	Heat stress (HS)
E_{Ref}	1901–2100	1901–2100	1901–2100	Irrigation on irrigated land, rainfed conditions in rainfed land	w/heat stress calculated using canopy temperature
E_{CO2}[a]	Fixed at 1900 level (296.8 ppm) for 1901–2005 and fixed at 2005 level (378.2 ppm) for 2006–2100	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}
E_{Cli}[a]	Same as in E_{Ref}	Recycle 1901–1920 for 1901–2005 and recycle 1996–2005 for 2006-2100	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}
E_{Nit}[a]	Same as in E_{Ref}	Same as in E_{Ref}	No N input application	Same as in E_{Ref}	Same as in E_{Ref}
E_{Irr}[a]	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}	No irrigation on irrigated and rainfed lands	Same as in E_{Ref}
E_{Man}	Same as in E_{Ref}	Same as in E_{Ref}	No N input application	No irrigation on irrigated and rainfed lands	Same as in E_{Ref}
E_{w/o_HS}	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}	w/o heat stress effect
$E_{w/\_HSAT}$	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}	Same as in E_{Ref}	w/heat stress calculated using air temperature

[a]We first run the model of the E_{Ref} case through the period 1901–2005. Then conduct environmental and management factor experimental simulations for the period 2006–2100.

level, whereas all other factors vary with time as in E_{Ref}. For the 2006–2100 sets, we first continue to run the model for the E_{Ref} case through the period 2006–2100. Next, we run the model from 2006 to 2100, with one of the four factors remaining fixed at the 2005 level, but other variable values are assumed to change as in the E_{Ref} case. In the E_{Nit} and E_{Irr} experiments, the N input or irrigation input is assumed to be zero, respectively. In the E_{Man} experiments, both N input and irrigation are assumed to be zero. We then estimate the effect of each factor by differencing the yields between the reference case and one of the five simulations: CO_2 fertilization (E_{Ref}–E_{CO2}), climate (E_{Ref}–E_{Cli}), irrigation (E_{Ref}–E_{Irr}), N input (E_{Ref}–E_{Nit}), and combined N input and irrigation (E_{Ref}–E_{Man}).

To identify and evaluate HS during reproductive stages, we performed two additional experiments. The first experiment is E_{w/o_HS}, which does not account for the HS effect. The second experiment, $E_{w/\_HSAT}$, accounts for the HS effect, but the effect is calculated using air rather than canopy temperature (Table 1). The effect of HS with canopy temperature and air temperature is calculated by subtracting E_{w/o_HS} and $E_{w/\_HSAT}$ from E_{Ref}.

For 1901–2005, we calculate the contribution of individual factors (in %) over a given time relative to the E_{Ref} case (e.g., both averaged over 1996–2005). For the two future scenarios, we compare the results for the 2090s (e.g., averaged over 2090–2099) relative to 1996–2005. The results are masked out using the irrigated and rainfed areas for each simulation at 0.5° x 0.5° (latitude x longitudes) spatial resolution. The total yield for each grid-cell is calculated by combining the weighted irrigated and rainfed yield (Equation S22 in Supporting Information S1). The results are presented at a spatial scale at 0.5° x 0.5° and a regional scale. To obtain the model results at regional scales, we average the spatial results for each crop over its cropland in six regions shown: NA, SA, EU, AF, CHN, and SSEA (Figure S1 in Supporting Information S1). It is to be noted here that the model simulates yield and production for all crop areas available in the literature. However, spatial plots do not display the yields and production for those grid cells that contain less than 0.1% of maize or soybean crop areas, such as some Canadian Prairies locations.

3. Results

3.1. Model Evaluation

Here, we evaluate the model performance for those processes, which are added in this study.

Table 2
Global and Regional-Scale Percent Bias (PBIAS, %) for Maize and Soybean Yields From the Original Version (Song et al., 2013), Revised Versions (This Study, E_{Ref}) of ISAM, and AgMIP Models Compared to Various Literature Data for 1996–2005[a]

	Maize				Soybean			
	PBIAS (%)			Yield (t/ha)	PBIAS (%)			Yield (t/ha)
Global/Region	Song et al. (2013) ($N = 23$)	This study[b] ($N = 23$)	AgMIP[d] ($N = 276$)	Literature data ($N = 23$)	Song et al. (2013) ($N = 23$)	This study[c] ($N = 23$)	AgMIP[d] ($N = 276$)	Literature data ($N = 23$)
Global	−20.7	9.5	−21.0	4.6	−30.5	4.9	−10.4	2.2
North America (NA)	−13.8	11.2	9.4	8.6	−24.2	−2.5	2.8	2.6
South America (SA)	−44.2	4.0	−86.6	3.1	−13.6	30.0	−15.3	2.4
Europe (EU)	−21.8	7.3	18.9	6.0	−4.6	15.7	27.1	3.0
Africa (AF)	−75.0	−4.3	−132.6	1.8	−94.5	2.4	−75.6	1.0
China (CHN)	−14.1	−7.4	−14.2	5.0	−81.6	−43.0	−31.7	1.8
South and South East Asia (SSEA)	−15.5	19.1	−96.4	2.2	−110.5	3.4	−80.7	1.0

Note. N is the number of values used to calculate PBIAS.
[a]The literature data set are Iizumi et al. (2014) for the period 1996–2005, Monfreda et al. (2008, M3) for the year 2000, You et al. (2014, MapSPAM2000 & 2005) for the years 2000 and 2005, and FAOstat (2017) for period 1996–2005. So, there are $N = 23$ sample literature data values (see Section 2.3). [b]The Original and Revised columns are the % bias (PBIAS) for w/o and w/ N stress effect on carbon allocation for maize (Text S4 in Supporting Information S1) and heat stress impact (Text S5 in Supporting Information S1). [c]The Original and Revised columns are the % bias (PBIAS) for w/o and w/ N stress effect on carbon allocation (Text S4 in Supporting Information S1), seeding rates (Text S2 in Supporting Information S1), heat stress impact (Text S5 in Supporting Information S1), and revised elevated CO_2 effect (Text S3 in Supporting Information S1) for soybean. [d]The AgMIP results are across 12 different crop models driven by AgMERRA with the default setting (Müller et al., 2019). For each model, 23 values are selected corresponding to the same years as literature data. So, there are $N = 276$ (=12 × 23) sample data values for the AgMIP case.

3.1.1. Crop Specific Planting Time and Seeding Rates

ISAM estimates crop-specific dynamic planting time decisions rather than fixed planting time at a grid-scale (Text S1 in Supporting Information S1). So, the dates can vary with time, depending upon the changes in the environmental conditions. Here, we evaluate the model estimated planting time using the literature data (Elliott et al., 2015) in Figure S7 in Supporting Information S1. ISAM results show that estimated planting time is controlled by climate and soil conditions (Table S1 in Supporting Information S1) associated with crop-specific phenology. In addition, we update the crop seeding rates and residue amount (Text S2 in Supporting Information S1), which vary with planting conditions (Table S2 in Supporting Information S1). The updated seeding rates at the sowing time are usually lower for soybean in CHN, AF, and SSEA. After implementing these modifications, modeled soybean yields are reduced. The revised yields in these regions for the 1996–2005 average compare better with the literature data. The percent bias (PBIAS, Text S10 in Supporting Information S1) of the modeled yield is reduced (Table 2).

3.1.2. CO_2 Fertilization Effect

Crop productivity under elevated [CO_2] from the original version of ISAM compared with measurements at FACE sites (Table S3 and Text S3 in Supporting Information S1 for FACE site calculations) shows that while the modeled yield for maize is consistent with FACE site measurements (Table S4 in Supporting Information S1), it is overestimated for soybean (Figure S8a and Table S4 in Supporting Information S1). This overestimation is because the electron transport rate calculations did not account for the curvature of the light response curve, resulting in the overestimation of photosynthesis, canopy temperature, and stomatal conductance (Figures S8b and S8c in Supporting Information S1). However, after implementing curvature to the light response curve (see the detailed description of the method and results in Text S3 in Supporting Information S1), the revised ISAM results under irrigated conditions are consistent with measured values. While the range of AgMIP model results under irrigated conditions for maize is comparable to the FACE experiment results but unable to calculate the reduction in maize yield. However, ISAM can calculate maize yield reduction as observed in the FACE experiment (Table S4 in Supporting Information S1).

3.1.3. N Fertilization Effect on Maize Yield

The ISAM model of Song et al. (2013) also overestimated the maize yields at the lower N application rates (Figure S9a in Supporting Information S1) because the model overestimates the carbon allocated to the grain formation under the N stress conditions (i.e., the ratio of N supply and N demand). However, model results for soybean are consistent with the measured data (Figure S9b in Supporting Information S1). After accounting the N stress effect on the carbon allocation to grain during initial and post-reproductive (grain-filling) stages of phenology (Text S4 in Supporting Information S1), the revised ISAM results for a lower N fertilizer rate at six sites (Table S5 in Supporting Information S1) show stronger N stress, and lower grain formation compared to the results estimated based on the original ISAM (Figure S9a in Supporting Information S1). These results, which are consistent with the field experiment studies, suggest that maize growth slows down at the lower N supply rates, causing a decline in yield (Alemayehu et al., 2015; Gehl et al., 2005; Getachew & Belete, 2013; Hammad et al., 2011). The revised model also improves the overestimation of simulated global and regional maize yields, particularly in AF, where N is a limiting factor (Table 2).

3.1.4. Heat Stress (HS) Effect

We implement HS in ISAM by accounting for the impact of HS on reducing carbon allocation during the reproductive phases of the phenology (Text S5 in Supporting Information S1). While other studies use air temperature for the calculation of the HS effect (Deryng et al., 2014; Teixeira et al., 2013), here, our model simulations consider the crop canopy temperature (Text S5 in Supporting Information S1), which is shown to explain better yield reductions associated with HS (e.g., Gabaldón-Leal et al., 2016; Siebert et al., 2014; Webber et al., 2017). To evaluate the model estimated yield performance with HS effect, we compared the three cases (E_{Ref}, E_{w/o_HS}, and $E_{w/\_HSAT}$) of correlation coefficients of 1982–2006 period detrended yields for ISAM and FAOstat (2017) (Table S6 and Figure S10 in Supporting Information S1). The results show that the ISAM simulated temporal variability for maize yields at global and regional scales is somewhat better in E_{Ref} than in E_{w/o_HS}. While the improvement in reproducing the observed temporal variability of maize yield occurs in all regions except for SA (Table S6 in Supporting Information S1), the differences between the two cases are small. The impact of HS on maize yield is more in AF and SSEA, where the temperature is higher than in other areas. Although maize growth also responds to HS calculated using air temperature, the resulting performance in capturing observed temporal variability in $E_{w/\_HSAT}$ is less than in E_{Ref} (Table S6 in Supporting Information S1). However, HS shows negligible effects on simulated soybean yield variability because of soybean's higher critical temperature (Text S5 in Supporting Information S1). Gourdji et al. (2013) showed that exposure to high critical temperatures in the reproductive period could happen in many places for maize but not for soybean in the twentieth century.

3.1.5. Percent Biases Results for ISAM

Overall, the PBIAS results show the model estimated yields at global and regional scales are compared well with the observations after model improvements, except for maize in SSEA (19%), soybean in CHN (−43%), and SA (30%) (Table 2). The PBIAS for maize yield is reduced from −21% to 10%, and for soybean from −31% to 5% globally. On the regional scale, modeled maize yield improves in NA, SA, EU, CHN, and AF, and soybean yield in NA, CHN, AF, and SSEA (Table 2). The remaining model biases might be due to the model limitations in estimating nutrients' limitation, crop mortality effects due to ozone, wind, hail, weeds, pests, disease, and/or due to not accounting for the cropping systems in the model. Also, uncertainty in the input data, such as climate, soil, or crop management, might have introduced the biases in the modeled yield (Barman et al., 2014a, 2014b; Kheshgi et al., 1999; Jagtap & Jones, 2002), which we plan to carry out in our future modeling analysis.

3.2. Model Estimated Crop Yields and Productions

3.2.1. Yields and Productions for the Historical Time

ISAM results for maize and soybean yields for the period 1996–2005 are compared with global data sets available in the literature (see Section 2.3) in Figure 1, and production on a 0.5° × 0.5° grid in Figure 2. Overall, the calculated global maize yield averaged from literature data sets is 4.6 t/ha (Table 2), with NA

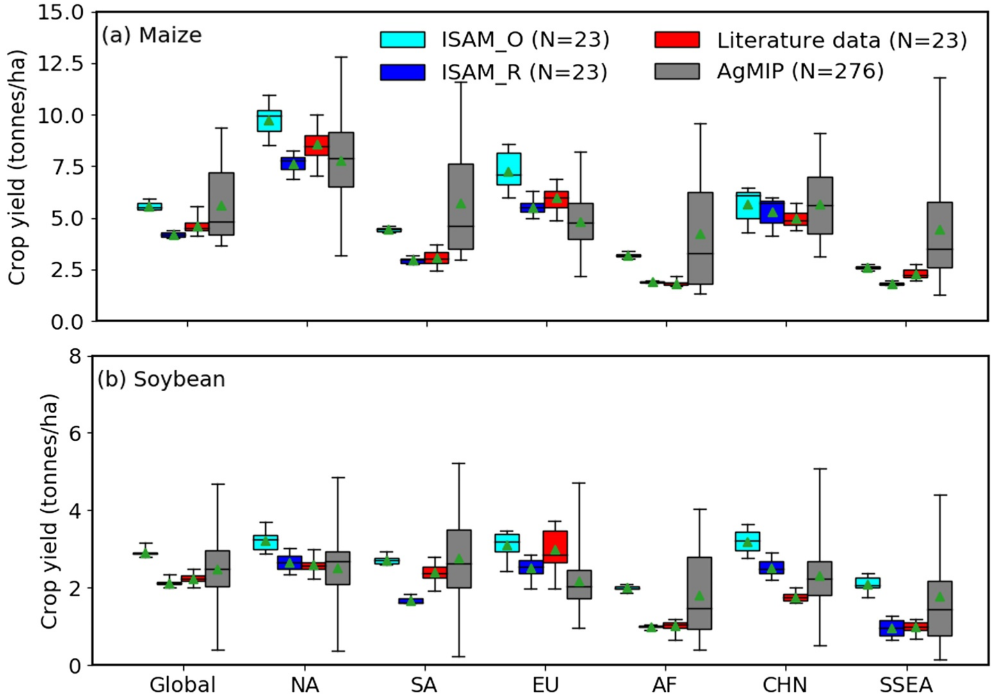

Figure 1. Global and regional-scale comparisons of (a) maize and (b) soybean annual yield (t/ha) from Integrated Science Assessment Model (ISAM), Agricultural Model Intercomparison and Improvement Project (AgMIP) (Müller et al., 2019), and the available data set values in the literature. Model results are the original (ISAM_O) and revised (ISAM_R) versions for the period 1996–2005, and the literature data include Iizumi et al. (2014) for years 1996–2005, Monfreda et al. (2008, M3) for 2000, You et al. (2014) for the years 2000 and 2005, and FAOstat (FAOstat, 2017) for years 1996–2005. The AgMIP results are values across12 different crop models driven by AgMERRA with the default setting (Müller et al., 2019). For each model, 23 values are selected corresponding to the literature data years values. The boxes are the interquartile ranges, the horizontal lines plotted in the boxes are the median values, and the whiskers indicate the highest and lowest values of the results. The green triangles marked in the boxes are the mean values.

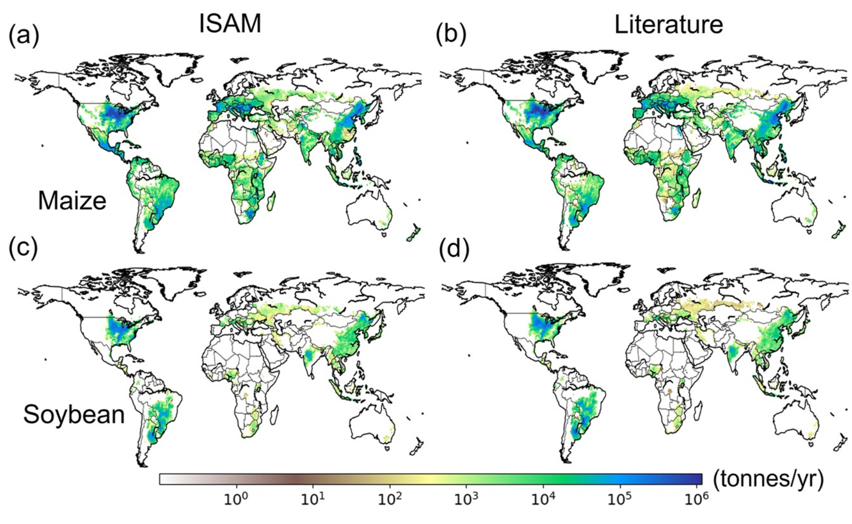

Figure 2. The spatial distribution of annual maize and soybean production estimated by ISAM averaged over the same years as literature data are compared to an average of literature data. The distribution is expressed in tonnes of annual production for each 0.5° × 0.5° grid-cell; the legend is, therefore, in units of tonnes/yr. The maize and soybean estimates from the Integrated Science Assessment Model (ISAM) model are weighted by irrigated and rainfed areas. The areas for both crops are masked by crop-specific areas. The literature data set is the average of three gridded products—Iizumi et al. (2014) for the period 1996–2005, Monfreda et al. (2008) for the year 2000, and You et al. (2014) for the year 2000 and 2005—as described in Section 2.3. The color scale is plotted on a logarithmic scale.

(8.6 t/ha) and AF (1.8 t/ha) are the highest and lowest yield regions. In contrast, global soybean yield is about half of the maize yield (2.2 t/ha), and regional values range between 1.0 t/ha in AF and SSEA and 3.0 in the EU (Table 2).

ISAM results for higher maize yield regions (NA, EU, and CHN) and lower maize yield regions (AF, SA, and SSEA) are within the range of observed contemporary yields (Figure 1a). ISAM also reproduces the measured pattern of soybean yields (Figure 1b) across high yield regions (NA, SA, and EU) and low yield regions (e.g., SSEA). Moreover, ISAM appears to capture the maize and soybean breadbaskets, including the Corn Belt in the United States, Argentina (Buenos Aires, Entre Rios, Cordoba, and Santa Fe), Brazil (Parana, Goias, Mato Grosso, and Minas Gerais), India (Madhya Pradesh, Maharashtra, and Rajasthan), and northeastern CHN (Figure 2). As also shown and discussed in the PBIAS section, the agreement between ISAM results and literature data is improved in the revised version of ISAM (ISAM_R), compared to the version of ISAM developed by Song et al. (2013), which is referred to as the original version of ISAM (ISAM_O) in Figure 1.

While ISAM captures similar patterns of literature data for maize and soybean productions (Figure 2) with higher production in grid cells with a higher cultivated area (Figure S3 in Supporting Information S1), some mismatches between modeled and literature spatial distribution data for harvested areas may have introduced some differences in production patterns. In general, the model underestimates maize production in the Corn Belt of the United States and north CHN, soybean production in Argentina, Brazil, and overestimates soybean production in northeastern CHN, and both production in Russia (Figure 2). Given that harvested crops' quantity and spatial patterns differ among the three literature gridded products applied here, the uncertainty for aggregated literature data values increases at the grid cell level (Porwollik et al., 2017). Therefore, it is perhaps not surprising that modeled production and yields of maize and soybean for some regions exhibit some differences from literature data.

3.2.1.1. Modeled Versus Measured Detrended Yield For 1982–2006

In addition, ISAM is able to reproduce the observed (FAOstat, 2017) detrended global and regional yields (Text S11 in Supporting Information S1 describes the method to calculate detrended yield) over the period 1982–2006 with the correlation coefficient, r, 0.7 for maize and 0.6 for soybean (Table S6 and Figure S10 in Supporting Information S1). These values are close to the middle of the range of values estimated based on the ensemble of global AgMIP model results (14 different model results for maize yield and 13 models results for soybean yield); 0.26–0.89 for maize and 0.00–0.64 for soybean (Müller et al., 2017) although crop areas and climate forcing are different. The model estimated detrended yields for both crops at the regional scale are also compared well with FAOstat (2017), except the values of r for soybean in AF, SSEA, and CHN and for maize in SSEA where ISAM estimated detrended values are higher than FAOstat (2017). The studies suggested that this might be related to the reporting year issue; some crop yields harvested at the end of the calendar year are reported by FAOstat (2017) in the following year report. Therefore, the detrended FAOstat yield might have a one-year delay in contrast to ISAM values in some years.

3.2.1.2. Comparison With AgMIP Model Results

Compared to literature data, 12 AgMIP crop model results for yields varied widely. However, an ensemble of the 12 model results compared better to literature data than the individual model results. Although the median of all AgMIP models gives better performance than the literature data (Figure 1), the estimated PBIASs for global and regional cases are higher than ISAM (Table 2), except for NA for maize and SA and CHN for soybean. The AgMIP models' simulated maize and soybean yields are out of the maximum range value reported by literature data in AF (PBIAS of −133% for maize and −76% for soybean) and SSEA (PBIAS of −96% for maize and −81% for soybean), where the actual productivity is low. Overestimating and underestimating crop yields from AgMIP models in these and other regions may be due to some processes and factors not considered in AgMIP models at the global scales, such as management practices, seeding rates, residue amount, and nutrient application (Müller et al., 2017).

3.2.2. Crop Yield Under RCP4.5 and RCP8.5 Scenarios

ISAM-estimated global crop yield changes are driven by environmental and management factors specified by scenarios RCP4.5 and RCP8.5. Changes in yield in the 2090s relative to that in 1996–2005 are shown in

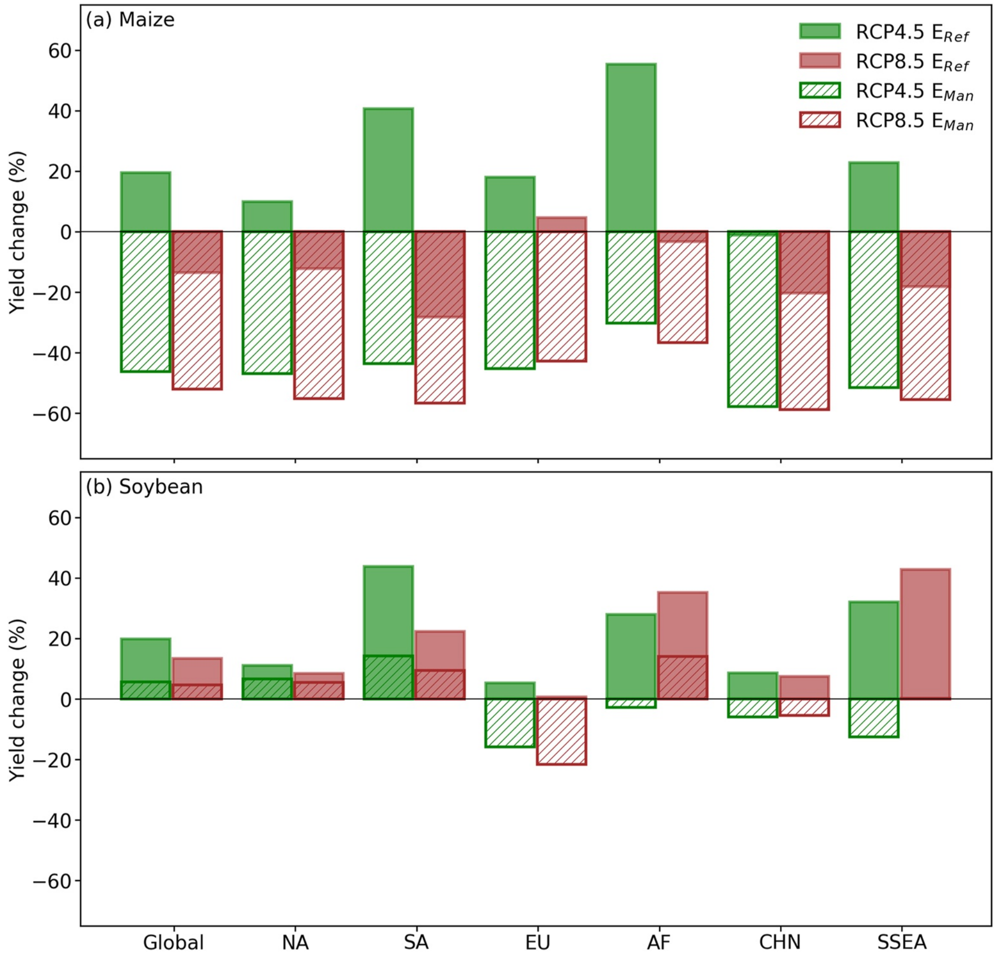

Figure 3. (a) Maize and (b) soybean yield changes (%) at regional and global scales for the 2090s relative to the 1996–2005 average under RCP 4.5 (green bars) and RCP 8.5 (brown bars) scenarios. Solid bars are results for E_{Ref} and crosshatched bars are results for E_{Man}.

Figure 3 and spatial maps in Figure S11 in Supporting Information S1. For scenario RCP8.5, the estimated maize yield for E_{Man} case is projected to decrease across all regions except for the EU. For scenario RCP4.5, maize yield is projected to increase in all regions, except for CHN (Figure 3a). In contrast, soybean yield increases across all regions under both scenarios (Figure 3b).

3.3. The Effects of Changes in Environmental and Management Factors on Maize and Soybean Yields

Each of the four environmental and management factors (CO_2, climate, N input, and irrigation) considered results in an estimated increase in maize and soybean yield at the global scale from 1901 to 1996–2005 (Table S7 for numbers and Figure S12a for maps in Supporting Information S1). The yields for both crops increase across all regions due to the CO_2 fertilization effect. However, the increase is stronger for soybean than for maize because for soybean, which is a C3 crop, photosynthesis is relatively less saturated under ambient [CO_2] (McGrath & Lobell, 2013). Without the [CO_2] increase, the global maize and soybean yields would have been lower by 5% and 19%, respectively (Table S7 in Supporting Information S1). Over the last century, climate change had a small positive global effect (1% and 4%), with some regions showing positive and negative effects (Figure S12a in Supporting Information S1).

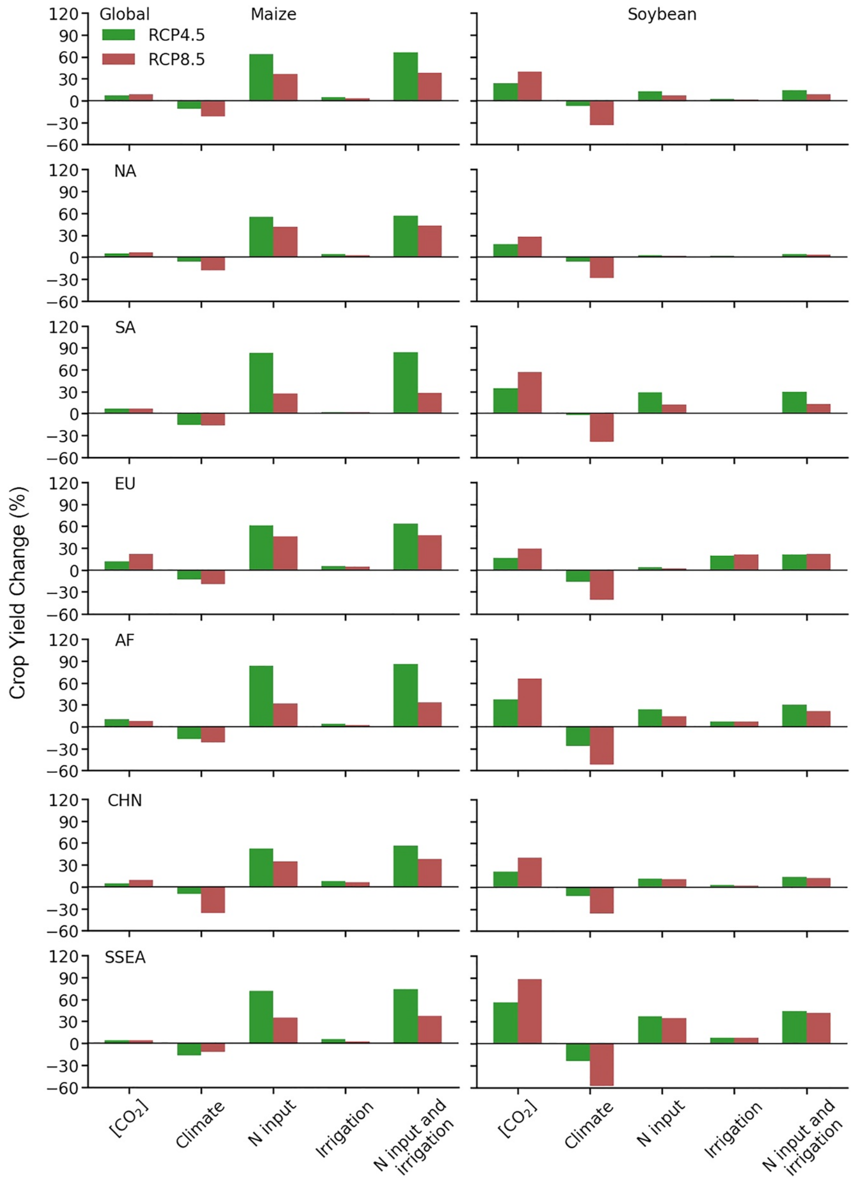

Figure 4. Maize and soybean yield contributions (%) for the average over the 2090s (2090–2099) at global and regional scales because of (CO_2), climate, N input, irrigation, and combined N input and irrigation under RCP4.5 and RCP8.5 scenarios (E_{Ref} in 2090s minus E_{XXX} in 2090s then divided by E_{Ref} in 1996–2005). E_{XXX} are the factor experiments shown in Table 1.

Out of the four factors studied here, N input increases the future maize yields, and [CO_2] affects the soybean yield the most under the two future scenarios (Table S7 in Supporting Information S1 and Figure 4). On the other hand, climate decreases the yields for both crops under the two scenarios. Irrigation shows a slightly positive effect across all regions.

Our results also reveal that management factors modulate the [CO_2] and climate effects on productivity for both crops. The increasing [CO_2] prompts higher crop yield but simultaneously requires more N, exacerbating N limitation. At the same time, although elevated [CO_2] promotes water use efficiency for crops, water is essential to maintain the increase in carbon assimilation and leaf area index, particularly for soybean. By implementing N and irrigation, crop yields show a higher response to elevated [CO_2] (Figure S13 in Supporting Information S1). These model results are supported by the experimental results (Gray et al., 2016; Kim et al., 2006; Ruiz-Vera et al., 2015). In general, higher response occurs in the regions where both effects of [CO_2] and management on crop yield are higher (Figures S12b and S12c in Supporting Information S1). Therefore, the synergistic effect of [CO_2] and management on crop yield is more positive in NA, EU, CHN for maize, and CHN and SSEA for soybean than in other locations (Figure S13 in Supporting Information S1). The effect is substantially higher in RCP8.5 than in RCP4.5.

Similarly, compared to climate change only effect, that is, without management case, interactive effects of management factors and climate change effect on crop substantially decreases/enhances crop productivity losses/gains in the 2090s (Figure S13 in Supporting Information S1). The N and water demand for crops increases under warmer and drier conditions. The demand also increases when the crop productivity is higher due to favorable environmental conditions. Therefore, crop growth shows a higher response in the 2090s than in recent years to management factors under both climate change scenarios.

4. Discussion

4.1. Model Evaluation Using Data

Global and regional crop yields estimated with the ISAM land surface model for the C3 crop soybean and the C4 crop maize are consistent with literature data averaged over 1996–2005 (Figures 1 and 2). ISAM-calculated yield variability at regional and global scales over time, 1982–2006, is consistent with FAOstat (2017) (Figure S10 in Supporting Information S1). In addition to this study, the overall confidence in ISAM estimated yields for maize and soybean is strengthened by validating ISAM results at the site level (Song et al., 2013) and the county level (Niyogi et al., 2015).

4.2. Estimated Effects of Environmental and Management Factors

ISAM results show that over the past century and for two future scenarios, RCP4.5 and RCP8.5, environmental and management factors affect maize and soybean yields:

4.2.1. CO_2 Fertilization

We find that the modeled CO_2 fertilization effect is stronger for soybean across all regions than for maize, because ISAM's net photosynthesis rate increases due to higher carboxylation rates and lower photorespiration rates for soybean than for maize. The effect is stronger in tropical regions (SA, AF, and SSEA) (Figure 4, Table S7 and Figure S12 in Supporting Information S1) because of (a) greater availability of N via N fixing bacteria (seen in measurements in Ainsworth et al., 2002), (b) smaller LAI (Figure S14 in Supporting Information S1), which absorbs higher photosynthetically active radiation (PAR), because PAR is inversely proportional to LAI (seen in measurements and model results in Sakurai et al., 2014), and (c) higher temperature enhances the CO_2 fertilization effect on net photosynthesis rate because both the specificity factor of Rubisco for CO_2 and solubility of CO_2 in water decline relative to O_2 (seen in measurements, Bernacchi et al., 2006; Ruiz-Vera et al., 2013) with rising temperature.

In contrast, the CO_2 fertilization effect is higher for maize in temperate drier regions (e.g., parts of NA, EU, AF, and CHN) in 1996–2005 (Table S7 and Figure S12a in Supporting Information S1). Rising [CO_2] can increase crop water productivity (the ratio of yield to evapotranspiration) due to the reduction in stomatal conductance, which indirectly enhances crop yield by ameliorating soil water stress in dry soils (seen in measurements in Leakey et al., 2006). Similar to the historical case, the yield increase is stronger for soybean than for maize under both future scenarios due to the CO_2 fertilization effect at regional and global scales in the 2090s (Figure 4, Figures S12b and S12c in Supporting Information S1 for maps).

We compared ISAM-estimated changes of global-average yield in 2080 for both crops with (w/) and without (w/o) CO_2 cases under RCP8.5 with model results available in the literature–AgMIP (Deryng et al., 2016) and NCAR's Community Land Model (CLM, Ren et al., 2018)—in Table 3. While ISAM-estimated maize and soybean yields for w/ CO_2 case falls within the interquartile range values of AgMIP model results, there are differences in the spatial patterns (Figure S15 in Supporting Information S1). This may be because the representation of management practices such as irrigation, crop residue, phenology, planting dates, and fertilizer application are different among AgMIP models (Deryng et al., 2016). For example, only three AgMIP models apply N fertilizer. Moreover, two models allow adaptation of planting time window (time

Table 3
Comparison of ISAM Estimated Global Maize and Soybean Yields Change to That of Other Model Results Available in the Literature: Percent Change in 2076–2085 (or 2080) Average Yield Relative to 1996–2005 (or 2000) Under the RCP8.5 Scenario

	ISAM		CLM[a]		AgMIP[b]	
Crop	w/ CO_2	w/o CO_2	w/ CO_2	w/o CO_2	w/ CO_2	w/o CO_2
Maize	−3.8	−10.1	0.7	−9.2	[−16.4; 1.0]	[−28.2; −13.3]
Soybean	25.1	−12.9	18.6	−9.6	[−12.1; 33.3]	[−40.5; −27.7]

Note. The results for reference w/ CO2 (ERef, Table 1) and w/o CO2 (ECO2, Table 1) cases are compared. The nitrogen input is applied as per the E_{Ref} experiments. The ISAM yield results are weighted by fixed irrigated and rainfed areas based on the MIRCA2000 data set, which are the same as other model results.

[a]Results are taken from Ren et al. (2018). N fertilization application is set at North American crop-specific levels everywhere and fixed over time. Then, yield is adjusted with nitrogen fertilizer assumptions based on FAO data. [b]Results are the interquartile range across all six global gridded crop models run with climate data from five global climate models (Deryng et al., 2016). The EPIC, GEPIC, and pDSSAT models apply fertilizer dynamically through the crop growing season: application occurs at specific stages of the crop development to consider the role of both application quantity and timing. PEGASUS applies fertilizer as a daily stress function and thus does not simulate the effect of fertilizer directly. LPJmL and LPJ-GUESS do not represent fertilizer application. PEGASUS and GEPIC allow for adaptation for variation of planting window with time, whereas the other GGCMs assumed fixed planting window overtime.

interval between the earliest and latest possible planting dates), while the other four models assume planting window to remain fixed with time at the present dates. By considering the climatic effect on planting time, crops in ISAM are planted earlier when the temperature is higher, which can alleviate high-temperature exposure through the growing season. As such, our global crop yield w/o CO_2 case is higher than AgMIP but is similar to CLM results that use the same CESM climate forcing (Table 3).

4.2.2. Climate Change (Excluding Heat Stress)

The climate effect on yield over the past century differs by region (Table S7 and Figure S12a in Supporting Information S1), but is in line with previous studies (e.g., Challinor et al., 2014; Fodor et al., 2017; Rosenzweig et al., 2014). The hotter temperature over most of the tropical and subtropical regions reduced yields for both crops, even though these regions experience higher precipitation. In contrast, increased temperature enhanced yields for both crops in colder regions (NA, eastern EU, northeastern CHN, and in boreal latitude zones) (Figure S12a in Supporting Information S1) in 1996–2005, where moderate warming increased the length of the growing period. For future scenarios, the adverse effect of climate lowers yields of both crops in all regions, with a stronger effect on soybean than on maize (Figure 4), because the optimum leaf temperature for photosynthesis is higher for maize than that for soybean. For example, net photosynthesis rate, *A*, for maize (soybean) increases up to 50 μmol $CO_2/m^2/s$ (25 μmol $CO_2/m^2/s$) with the leaf temperature that increases to 40°C (25°C); after that, *A* decreases with increasing leaf temperatures (Figure S16 in Supporting Information S1). Moreover, rising temperature increases crop respiration and reduces carbon use efficiency (CUE), defined as the ratio of net primary production to gross primary production (Zhang et al., 2013). Since soybean has lower CUE and shallower rooting depths than maize (Yamaguchi, 1978), soybean incurs relatively higher carbon losses through respiration, resulting in a much stronger response to climate change (Figure 4). CLM had also discovered a more negative impact on soybean than maize yield (Lombardozzi et al., 2018).

4.2.3. Heat Stress

ISAM estimated results show a higher global HS effect during the reproductive stages on maize yield (−2.4% and −5.9% under RCP4.5 and RCP8.5) than on soybean yield (−1.3% and −4.6% under RCP4.5 and RCP8.5) by the 2090s (Figure 5). While HS effect on yield is estimated in previous modeling studies using surface air temperature (e.g., Deryng et al., 2014; Teixeira et al., 2013), ISAM simulations are performed using canopy temperature rather than the surface air temperature because canopy temperature is warmer than the surface air temperature under drier and rainfed conditions. However, the canopy temperature is colder than the surface air temperature under irrigated conditions. So, the canopy temperature can ameliorate crop yield losses due to HS through irrigation. For example, the cooling effect of irrigation can decrease yield losses. The published global crop modeling studies, on the other hand, prescribed relatively warm air temperature (as opposed to canopy temperature while irrigating) for temperature and HS calculations. The model estimated heat stress-related agricultural hotspot regions are consistent with the published studies (Gourdji et al., 2013; Teixeira et al., 2013), which shows subtropical and temperate crop areas have large cropping areas under higher HS risk. ISAM results show that South Asia, Sahel, Eastern China, Spain, parts of Central Asia (e.g., Russian Federation), Central NA, Eastern Brazil, and Central SA are regions of high HS for maize yield (Figures 5a and 5c). A high HS effect on soybean yield is found in Central NA and SA, Northern India, Eastern CHN, and the Southwest region of Russia (Figures 5b and 5d).

To quantify crop yield risk level under HS due to projected climate change under two scenarios by the 2090s, we also estimate the coefficient of variation (CV), which is defined as the ratio of standard deviation to mean values of crop yield (Song et al., 2015). Yield risks increase if the variance is larger or the average yield is lower, the CV of crop yield becomes larger (i.e., lower temporal yield stability). Overall, global CV

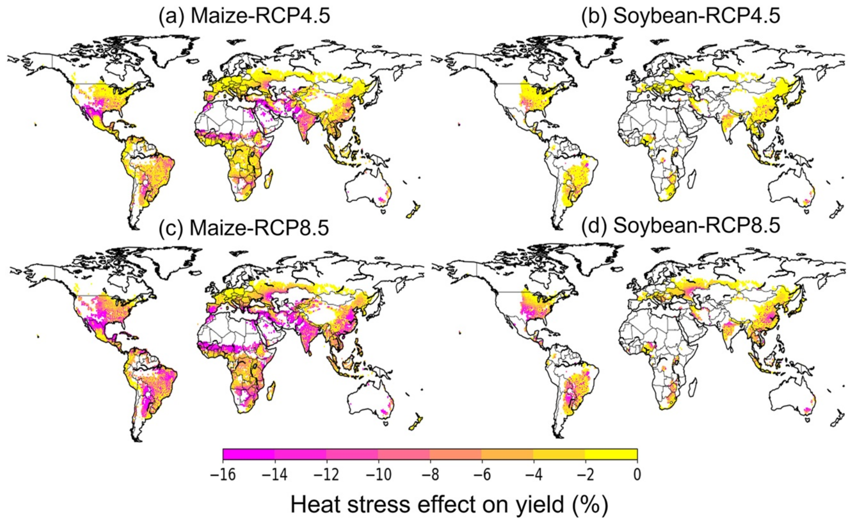

Figure 5. Maps of the effect of heat stress on maize (a and c) and soybean (b and d) yield (%) for RCP4.5 (a and b) and RCP8.5 (c and d) in the 2090s. Values show [(yield w/ heat stress minus yield w/o heat stress)/(yield w/o heat stress)]*100%.

is higher for soybean than that for maize and higher under RCP8.5 than under RCP4.5. The CV of maize and soybean yield for individual regions is greater in NA, EU, SSEA, and CHN than SA and AF (Table S8 in Supporting Information S1). Furthermore, CV becomes larger when considering HS (E_{Ref}) than without HS (E_{w/o_HS}) in the model (Table S8 in Supporting Information S1).

4.2.4. Irrigation

Irrigation enhances maize yield more than that of soybean over the last century and under the two future scenarios (Table S7 in Supporting Information S1 and Figure 4) because of a higher fraction of irrigated area for maize than that for soybean, which is also pointed out by Elliott et al. (2014) and Jägermeyr et al. (2015). The global maize yield with irrigation is estimated to increase by about 5%, whereas 3% for soybean over 1996–2005 (Table S7 in Supporting Information S1), although regional differences exist. Overall, our global results are consistent with previous field measurement studies (Chen et al., 2018; Verma et al., 2005), showing maize yield is more responsive to irrigation than for soybean because of the higher photosynthesis and productivity of maize. On a regional scale, the effects of irrigation over 1996–2005 are most obvious in arid and semiarid areas for both crops, including central and western parts of NA, northeastern CHN, Eastern Australia, Middle East, Central Asia, and western EU (Figure S12a in Supporting Information S1). Also, maize and soybean yields under the irrigated case do not change much in the tropical agriculture regions, that is, SA (Table S7 in Supporting Information S1), because of low irrigated areas and higher precipitation rates. In general, irrigation effect on crop yield becomes less under both scenarios and reduces more in RCP8.5 than RCP4.5. However, the magnitudes do not change much by the 2090s, except for soybean yield in the EU (Table S7 in Supporting Information S1 and Figure 4).

4.2.5. N Input

The effect of N input is stronger for maize than for soybean because soybean is an N-fixing crop (Figure 4, Table S7 and Figure S12 in Supporting Information S1). The stimulation of yield with N input is greater in N-limiting and high N-application regions, including NA, EU, and CHN. These regions are water-limiting regions too. Therefore, irrigation amplifies the N input effect by reducing the water stress effect and enhancing the root carbon that stimulates N uptake (Yang et al., 2009). The interactive N effect increases the yield for both crops in most regions by the 2090s. This is especially under the RCP4.5 scenario with a higher N input amount and improved N availability under favorable environmental conditions (Figure 4). The responses under RCP8.5 are lower because of lower nitrogen input rates per area (Figure S4 in Supporting Information S1) and warmer conditions, weakening the N input effect. The N fertilizer intensification can enhance crop yield in current low-productive regions, such as AF for maize and soybean (Figure 1). The model results show that agriculture practices in AF result in higher N losses than N added to the soils, which are consistent with other studies (e.g., Lassaletta et al., 2014; Liu et al., 2010; Vitousek et al., 2009). This can be because farmers in AF are considering N management practice, such as 85 percent residue removal at the harvest time (Folberth et al., 2012), which we also simulate in ISAM for the AF region (Text S2 in Supporting Information S1). The model result shows that yields for both crops are increased more under RCP4.5 than the RCP8.5 scenario due to intensified N application rates in the 2090s, especially in AF and SA (Figure 4, Figures S12b and S12c, and Table S7 in Supporting Information S1).

4.2.6. Synergistic Effects on Crop Yield

ISAM results confirm that management factors help offset some of the adverse effects of climate change and limitations of resources (e.g., water and N). However, the interaction between C, water, temperature, and N can be nonlinear; it is expected to produce combined effects than the sum of their individual effects on crop yields. An example here is that the combined effect of N input and irrigation on crop yield is not an additive response of individual forcings. Over the historical time, irrigation and N input offset the decrease in crop yields otherwise caused by drier and N-limitation conditions and increased yield from CO_2 fertilization (Table S7 in Supporting Information S1). When the N and irrigation forcings are combined, synergistic effects enhance crop yields such that the combined effect of N and irrigation on crop yield is more than their individual sum (Figure 4).

Moreover, ISAM results show that crop productivity is colimited by environmental factors, such as $[CO_2]$ and climate. Therefore, management factors under the higher $[CO_2]$ and warmer future climate scenario RCP8.5 may not be able to offset all the crop yield losses by the end of this century. This is the case, for example, for global maize yield w/management case under the RCP8.5 scenario, where yield is estimated to be about 14% lower in the 2090s than in 1996–2005 (Figure 3). These results show that management practices through N and irrigation under socio-economic assumptions of the RCP8.5 scenario and dynamic planting time decisions do not fully compensate for the loss of crop yield from environmental drivers, suggesting the need for more climate change adaptation in the agriculture sector over this century.

4.2.7. Summary and Future Directions

This study aims to quantify the relative importance of two major environmental factors and their interactive effects with management factors and the effect of extreme heat stress on model-estimated productivity of maize and soybean. Our study also provides state-of-the-art estimates of spatial and temporal distributions of crop yield responses to critical high temperature in the reproductive period by identifying heat stress using canopy temperature. As a first step, we show that the model estimated effects of various environmental and management factors on crop yields and their variability in the twentieth century compare well with literature data sets on the global and regional scale.

Accounting for management factors' effects, including those prescribed by the SSPs, model results show that, by 2090s, global maize yield declines by 14% under RCP8.5 and increases under RCP4.5, while soybean yield increases by 20% under RCP4.5 and by 13% under RCP8.5. Yet Kriegler et al. (2017) find that global cereal crop yield would need to increase by 60% between 2005 and 2100 under both scenarios to fulfill future food demand. These results suggest that the management practices considered in this study for maize and soybean will not be sufficient to satisfy the future food demand, implying that additional advanced technologies and management practices will be needed to intensify crop productivity in the future.

Looking beyond this study, we plan to improve the treatment of management practices so that observed yield and future trend projections can be improved (cf., Alexandratos & Bruinsma, 2012). For instance, ISAM does not consider different irrigation sources (such as irrigated water from groundwater pumping) and pathways (flood irrigation, drip irrigation, and sprinkler irrigation), which may affect hydrological cycles (Jägermeyr et al., 2015; Leng et al., 2017). Thus, improving water use processes for each crop type in the model can improve the estimation of global human water usage, crop yield, and irrigation demand for crops (Webber et al., 2016). Additionally, it should be noted that the input data such as climate and N inputs are primary but inevitable sources of uncertainties in the estimated future crop yields. In the future analysis, we plan to study the crop yields using the ensemble of multimodel results rather than single model results. We also plan to correct model simulated precipitation fields, including variability and other higher moments, using different bias correction approaches (e.g., Cannon, 2016; Li et al., 2010). Although we use state-of-the-art N input data under SSPs from Coupled Model Intercomparison Project Phase 6 (CMIP6) (Lawrence et al., 2016), future studies should consider different N application methods, forms, timing, and levels. These advancements and additional model analyses with other crops are needed to mitigate the effects of climate change and extremes on the agriculture system.

Conflicts of Interest

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

Data Availability Statement

We provide the following data sets: (a) Spatial distribution of mean maize and soybean production (unit: tonnes/year for a 0.5° x 0.5° grid) from ISAM simulations and literature averaged for the time period 1996–2005 (Figure 2). (b) Spatial distribution of irrigated and rainfed areas for maize and soybean (unit: fraction of grid cell) for 1990–2015. (c) Spatial distribution of N fertilizer (unit: kgN/ha for 0.5° x 0.5° grid) applied over the maize and soybean areas for 1990–2100. The data for 2016–2100 are based on scenarios. (d) ISAM simulated the spatial distribution of maize and soybean yields (unit: t/ha) based on various model experiments described in Table 1. All the data are stored in NetCDF files. The data can be accessed from the ISAM website: http://climate.atmos.uiuc.edu/Lin_Cropyields/.

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