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Key Points:

- This is the first multi-crop model assessment of stratospheric aerosol climate intervention (SAI) impacts on global agriculture
- Two crop models show that SAI benefits global maize relative to climate change, and the third crop model shows a very mild response to SAI
- Changes to diffuse radiation in this scenario have a small impact on global maize, while temperature changes dominate the overall response

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Maize Yield Changes Under Sulfate Aerosol Climate Intervention Using Three Global Gridded Crop Models

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Abstract As the severity of climate change and its associated impacts continue to worsen, schemes for artificially cooling surface temperatures via planetary albedo modification are being studied. The method with the most attention in the literature is stratospheric sulfate aerosol intervention (SAI). Placing reflective aerosols in the stratosphere would have profound impacts on the entire Earth system, with potentially far-reaching societal impacts. How global crop productivity would be affected by such an intervention strategy is still uncertain, and existing evidence is based on theoretical experiments or isolated modeling studies that use crop models missing key processes associated with SAI that affect plant growth, development, and ultimately yield. Here, we utilize three global gridded process-based crop models to better understand the potential impacts of one SAI scenario on global maize productivity. Two of the crop models that simulate diffuse radiation fertilization show similar, yet small increases in global maize productivity from increased diffuse radiation. Three crop models show diverse responses to the same climate perturbation from SAI relative to the reference future climate change scenario. We find that future SAI implementation relative to a climate change scenario benefits global maize productivity ranging between 0% and 11% depending on the crop model. These production increases are attributed to reduced surface temperatures and higher fractions of diffuse radiation. The range across model outcomes highlights the need for more systematic multi-model ensemble assessments using multiple climate model forcings under different SAI scenarios.

Plain Language Summary Human activities are continuing to put planet-warming greenhouse gases into the atmosphere. Increasing the amount of sulfate aerosols in the stratosphere has been proposed as a way to reflect a small portion of incoming solar radiation to temporarily cool the Earth's surface temperature and, therefore, mitigate the impacts of climate change. However, these reflective particles cause complex atmospheric feedback mechanisms that may lead to societal and Earth system impacts that are difficult to predict, including impacts on global food production. As a pilot study, we explore impacts on global maize productivity using state-of-the-art mechanistic climate and crop models and highlight that more research on this topic is still needed before informed decisions can be made.

1. Introduction

Climate change has already had a large impact on the world's agricultural production, which is anticipated to amplify as global anthropogenic greenhouse gas emissions continue to increase (Jägermeyr et al., 2021; Mbow et al., 2019). Climate change projections and associated impacts have accelerated research on climate intervention (also called solar radiation modification) strategies (National Academies of Sciences, 2021). One strategy gaining the most attention in the literature is Stratospheric Aerosol Intervention (SAI). SAI would temporarily increase Earth's albedo by placing reflective sulfate aerosols in the stratosphere, blocking part of the sunlight reaching Earth's surface and, hence, reducing surface temperatures (NASEM, 2021), the same cooling mechanism as after large volcanic eruptions (Crutzen, 2006). This intervention strategy would impact the entire Earth system, leading to changes in plant growth, and thus agricultural production, and affecting the surface energy balance and hydrologic and carbon cycles.

SAI would create a new and unique environment for plants. SAI would counteract climate change-related temperature increases, while modifying other climate patterns such as precipitation and radiation and would

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maintain greenhouse-gas-induced CO_2 fertilization effects on plants, therefore creating an unprecedented and difficult-to-predict climatic profile (NASEM, 2021). Persistent sulfate aerosols in the stratosphere would reduce total solar radiation that reaches the surface and, thereby, reduce surface temperature, while also scattering incoming solar radiation and increasing diffuse radiation (NASEM, 2021). SAI has no direct effect on atmospheric CO_2 concentrations, although the interactions with land and ocean through physical, chemical, biogeophysical and biogeochemical processes could change CO_2 fluxes and, thus, slightly impact the atmospheric CO_2 concentration (Zhao et al., 2024). Therefore, in this study, we assume that CO_2 concentrations under the climate change scenario and the SAI scenario are the same. Increasing CO_2 is likely to benefit C_3 crops such as rice, soybean, and wheat due to their photosynthesis being limited by CO_2 uptake (Farquhar et al., 1980). However, C_4 crops like maize have a different leaf structure that allows them to concentrate CO_2 around the Rubisco enzyme, reducing their photorespiration (Collatz et al., 1992). This means that maize will benefit less from increasing atmospheric CO_2 than other major crops, making climate change impacts more severe (Jägermeyr et al., 2021). Another unique environmental condition caused by SAI is enhanced diffuse radiation, leading to higher light absorption rates for plants, and, therefore, creating a radiation fertilization effect (Greenwald et al., 2006; Gu et al., 2003; Schiferl et al., 2018).

Previous modeling studies looking at SAI impacts on global agriculture have always used one crop model, either process-based or statistical, and have produced diverse findings, as those studies focus on different regions and crops under various SAI scenarios. In general, most studies found that SAI would benefit or have a minimal impact on agriculture relative to climate change (Clark et al., 2023; Fan et al., 2021; Grant et al., 2025; Pongratz et al., 2012; Proctor et al., 2018; Xia et al., 2014; Zhan et al., 2019). However, one study did find a negative impact on Indian groundnut under climate intervention relative to climate change, due to precipitation reduction (Yang et al., 2016). It is important to compare impacts to global agriculture from the same SAI scenario across multiple crop models, as it has been shown that global process-based crop model responses to future climate change vary widely (Jägermeyr et al., 2021; Rosenzweig et al., 2014). Understanding the variation in crop model responses to SAI, including diffuse radiation fertilization, is valuable to reduce the uncertainties in agriculture system responses to SAI. Communicating potential impacts and uncertainties of global agriculture from SAI is important for informing policymakers and ensuring knowledgeable decision making.

This study uses three global process-based crop models: the Community Land Model version 5 crop model (CLM5crop; Lombardozzi et al., 2020), the Lund-Potsdam-Jena General Ecosystem Simulator crop model (LPJ-GUESS; Lindeskog et al., 2013), and the Decision Support System for Agrotechnology Transfer global crop model v4.8.0 (pDSSAT; Elliott et al., 2014; Hoogenboom et al., 2019) to study maize yield changes under the future climate warming scenario SSP2-4.5 and the Assessing Responses and Impacts of Solar climate intervention on the Earth system with stratospheric aerosol injection (ARISE-SAI; Richter et al., 2022). The ARISE-SAI scenario uses SAI to maintain a global average temperature increase of 1.5°C above preindustrial levels under SSP2-4.5. SSP2-4.5 represents a continuation of the Representative Concentration Pathway 4.5 (RCP4.5) scenario and closely reflects current policy scenarios (Burgess et al., 2021). This scenario envisions a future where social, economic, and technological trends follow historical patterns without major shifts, positioning it as an intermediate mitigation scenario within the medium range of future forcing pathways (O'Neill et al., 2017). 1.5°C above preindustrial is one of the climate change targets set at the international negotiations at the 21st Conference of the Parties (COP21). The selection of reference case and temperature target of SAI make this scenario more policy-relevant as it implements a more moderate amount of SAI under a "middle-of-the-road" future climate scenario to meet a defined policy goal, rather than simply aiming to achieve a large signal-to-noise ratio. The climate forcing is from SSP2-4.5 and ARISE-SAI simulations done by the Community Earth System Model version 2 (CESM2). Here, we aim to understand the differences between crop models responses to a specific SAI implementation and highlight the importance of multi-crop model and multi-climate model assessment before drawing conclusions of SAI impacts on agriculture.

2. Methods

2.1. Climate Model Simulations

In this study, the atmospheric forcing used as input for the global crop models was from CESM2 (Danabasoglu et al., 2020) using the Whole Atmosphere Community Climate Model Version 6 (WACCM6) configuration. The background climate change scenario followed the Shared Socioeconomic Pathway (SSP) 2, with Representative

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Concentration Pathway 4.5, hereafter SSP2-4.5 (Meinshausen et al., 2020). CESM2 was run at 1.25° by ~0.9° longitude-latitude resolution with 70 vertical levels that extend up to 140 km above the surface. WACCM6 has comprehensive stratospheric and tropospheric chemistry and dynamics to simulate the impact of SAI on surface temperature, precipitation, humidity, and direct and diffuse radiation. SO_2 is injected every year within the model into one grid box at about a 21.5 km height at four different latitudes: 30°N, 15°N, 15°S, and 30°S. The location and amount of SO_2 injection is determined through a feedback control algorithm that attempts to maintain three objectives simultaneously: global mean temperature the same as during 2020–2039, which in this model is 1.5°C above preindustrial; the interhemispheric temperature gradient during 2020–2039; and the equator-to-pole temperature gradient during 2020–2039. SAI starts in the year 2035, and we use the years 2016–2025 of SSP2-4.5 as our reference period. Although CESM2 ran SSP2-4.5 and ARISE-SAI for 10 ensemble members, there are only five of them that have the right climate variables saved for offline crop model simulations. Here, we used one ensemble member from the five ensemble simulations from CESM2 for this pilot project. Additional details on the climate model simulations can be found in Richter et al. (2022).

2.2. Crop Model Simulations

To understand impacts to global maize productivity under both climate change and SAI scenarios, we use three different well-developed global process-based crop models: version 5 of the CLM crop model (CLM5crop), LPJ-GUESS, and pDSSAT v4.8.0 (Elliott et al., 2014; Hoogenboom et al., 2019; Lawrence et al., 2019; Lindeskog et al., 2013). We chose one ensemble member each from the CESM2(WACCM6) simulations of SSP2-4.5 (2016–2068) and SSP2-4.5 with SAI (2036–2068) to force the three crop models, with 2016–2025 of SSP2-4.5 serving as the reference period. The climate model forcing was downscaled to 0.5° by 0.5° longitude-latitude resolution. LPJ-GUESS and pDSSAT are forced by daily atmospheric inputs, while CLM5crop was run with 3-hourly and 1-hourly data. Crop model simulations followed transient CO_2 concentrations under SSP2-4.5 (Meinshausen et al., 2020). Other inputs such as planting date, cropping area, nitrogen fertilizer application rates and dates, and atmospheric NO_3 and NH_4 deposition were held constant at 2015 levels following the Global Gridded Crop Model Intercomparison phase 3 protocol (Jägermeyr et al., 2021; Portmann et al., 2010). This means that all impacts to maize production are driven solely by changes to the climate. All crop models simulate maize under both rainfed and fully irrigated conditions. All three crop models were previously evaluated against historical period yield observations and were found to be able to represent global historical maize yields, supporting their use for projections of maize productivity under future climate conditions (Clark et al., 2023; Jägermeyr et al., 2021; Müller et al., 2017). Simulated yields for all three crop models were evaluated against reported global yield observations from the Food and Agriculture Organization of the United Nations (FAO, 2024). Müller et al. (2017), which used an older version of CLMcrop, forced the crop models with the AgMERRA weather data set (Ruane et al., 2015), while Jägermeyr et al. (2021) and Clark et al. (2023) used historical weather data from the Global Soil Wetness Project Phase 3 (Dirmeyer et al., 2006). Historical simulations used for model evaluation were run from 1980 to 2010 at $0.5 \times 0.5°$ resolution for LPJ-GUESS and pDSSAT (Jägermeyr et al., 2021; Müller et al., 2017) and $2.0 \times 2.0°$ resolution for CLM5crop (Clark et al., 2023). The data used for calibration of crop model parameters such as photosynthetic capacity, leaf area index, phenology, and carbon-nitrogen allocation vary between crop models (Lawrence et al., 2019; Lombardozzi et al., 2020; Müller et al., 2019). CLM5crop is limited by lacking any spatiotemporal parameterization and uses a fixed global parameterization for each crop type, limiting its ability to accurately represent a wide range of agricultural practices relative to other crop models (Lombardozzi et al., 2020). While all three models are calibrated to reproduce the same sowing dates and growing season lengths using the Global Gridded Crop Model Intercomparison (GGCMI) crop calendar (Jägermeyr et al., 2021), differences between models in the calibration of other key parameters can add to divergent model responses and introduce uncertainty. While LPJ-GUESS is not able to partition between direct and diffuse radiation, CLM5crop and pDSSAT had additional simulations that isolated the impact of enhanced diffuse radiation fertilization under SAI. pDSSAT ran the climate change and SAI scenarios with either prescribing total incoming shortwave solar radiation (default) or a novel partitioning between direct and diffuse shortwave radiation. Since the pDSSAT CSM-CERES-Maize model calculates daily photosynthesis using radiation use efficiency (RUE) (Jones and Kiniry, 1986), the partitioning between direct and diffuse radiation is based on the fractional change in RUE as a function of the diffuse fraction (DF) detailed in Greenwald et al. (2006). This approach is like the pDSSAT diffuse radiation response from Schiferl et al. (2018). A maximum change in RUE of 50% at DF of 0.8 is used to prevent overestimation of plant growth (Greenwald et al., 2006). The diffuse fraction is calculated as:

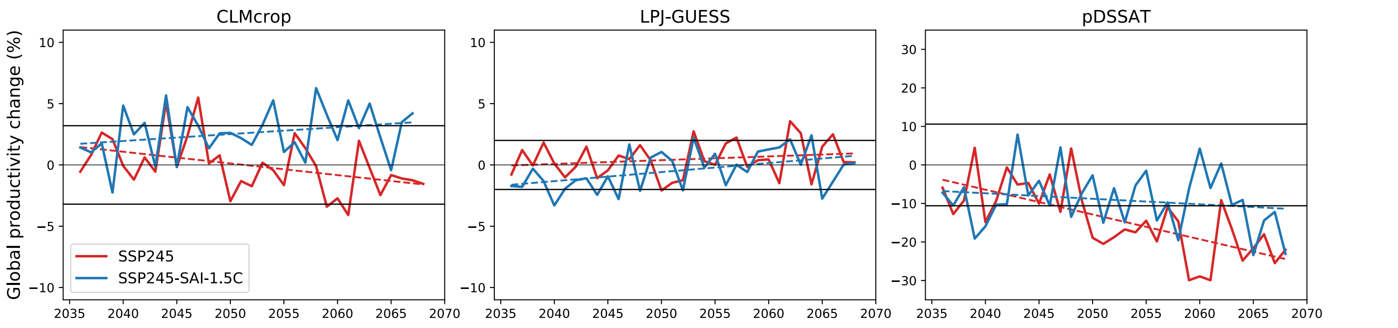

Figure 1. Time series of global maize production changes under the climate change scenario SSP2-4.5 and the corresponding SAI scenario SSP2-4.5-SAI-1.5C relative to the reference period of 2016–2025 for each of the three crop models CLM5crop, LPJ-GUESS, and pDSSAT. Horizontal black lines above and below zero indicate the standard deviation of production variability over the reference period for each model. Colored dashed lines are trendlines of time series data for each scenario.

$$\mathrm{DF} = \frac{\mathrm{SDIF}}{\mathrm{SRAD}} \tag{1}$$

where SDIF is the daily diffuse shortwave solar radiation (MJ m^{-2}) and SRAD is the daily total incoming shortwave solar radiation (MJ m^{-2}) provided from CESM2. The fractional change in RUE with a maximum change of 50% is calculated as:

$$\mathrm{RUE_{dif}} = \mathrm{RUE} * \left(1 + \left(1.21 * \mathrm{DF}^3 - 3.26 * \mathrm{DF}^2 + 2.92 * \mathrm{DF} - 0.37\right)\right) \tag{2}$$

where RUE_{dif} is the daily RUE with diffuse radiation effect (g MJ^{-1}), RUE is the default maize-specific parameter (g MJ^{-1}), and the constants are from Greenwald et al. (2006). Daily potential dry matter production (PCARB, g) is then calculated via:

$$\mathrm{PCARB} = \mathrm{IPAR} * \mathrm{RUE_{dif}} * \mathrm{PCO2} \tag{3}$$

where IPAR is the daily intercepted photosynthetically active radiation (MJ) and PCO2 is the crop-specific CO_2 effect on growth rate (Jones and Kiniry, 1986). If SDIF is not provided, the model uses the default RUE processes.

CLM5crop ran simulations that tested the impact of changing the direct/diffuse ratio under SAI relative to climate change. This was done by first reducing the total solar radiation of SSP2-4.5 to equal that of ARISE-SAI. Then the direct and diffuse radiation of SSP2-4.5 was replaced by the direct and diffuse radiation of ARISE-SAI. This allows the impact of just changing the direct/diffuse ratio under SAI to be understood while ignoring changes to total solar radiation. These additional radiation-partitioned scenarios allow the impact of diffuse radiation fertilization on global maize production under SAI to be tested in these two models.

3. Results

3.1. Crop Model Comparison of Maize Production Responses to SAI

Figure 1 shows the annual time series of global maize production change under both climate change scenario SSP2-4.5 and climate change with SAI implemented to maintain 1.5°C above preindustrial levels (SSP2-4.5-SAI-1.5C) relative to the reference period (2016–2025). CLM5crop and pDSSAT show very similar responses to interannual variability of production under climate change scenario SSP2-4.5 (Figure 1). CLM5crop and pDSSAT show a decrease in maize production over time under SSP2-4.5 relative to the reference period, while LPJ-GUESS shows almost no trend (Figure 1). The response to SAI varies between models. Compared with SSP2-4.5, CLM5crop and pDSSAT show a benefit to production of 4% and 11% under SAI over the years 2049–2068, while LPJ-GUESS shows a difference in global production of 0% between the two scenarios during the same time period (Figures 1 and 2). In CLM5crop, this increase to production under SAI causes the global production of maize to increase relative to the reference period, while in pDSSAT the change to global production under SAI is still a decrease of about 10% relative to the reference period (Figure 2). LPJ-GUESS exhibits a

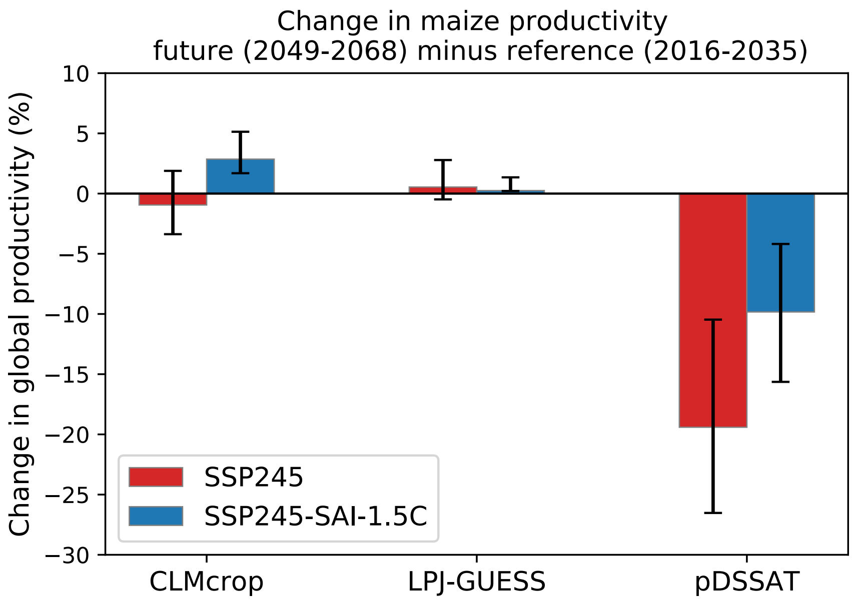

Figure 2. Percent change to global maize production in the three crop models under future (2049–2068 average) climate change and SAI relative to the reference period of 2016–2025. Error bars indicate the 25th and 75th percentiles of the data to highlight the interannual variability, that is, the model uncertainty related to "noise" within the climate and crop model simulations.

stronger response to elevated atmospheric CO_2 concentrations and a weaker sensitivity to higher temperature resulting in positive yield changes under climate change, relative to other crop models like pDSSAT that show substantial declines in maize productivity (Jägermeyr et al., 2021; Müller et al., 2024). These models differ in process representation. For example, CLM5crop and LPJ-GUESS do not have mechanisms in place to accelerate crop senescence from extreme heat; heat stress is simulated in these models by only reducing photosynthesis and water use efficiency (Lawrence et al., 2019; Lindeskog et al., 2013). In addition to photosynthesis and drought stress, pDSSAT uses heat stress damage functions that accelerate crop senescence above certain temperature thresholds (Elliott et al., 2014; Hoogenboom et al., 2019). This means that impacts from extreme temperature would tend to be stronger under both future climate change and SAI in pDSSAT when compared to CLM5crop and LPJ-GUESS, resulting in exacerbated global production impacts in pDSSAT (Figures 1–3). pDSSAT also has one of the largest negative responses to future climate change in a recent study on future production impacts from 12 global gridded crop models (Jägermeyr et al., 2021), while LPJmL (a branched-off version using similar roots as LPJ-GUESS) had one of the smallest responses to future maize production, which is consistent with our findings (Figure 3). The changes to global maize production in CLM5crop and LPJ-GUESS under both climate change and SAI still mostly fall within one standard deviation of interannual variability in the reference period and are, therefore, not as significant as changes in pDSSAT (Figure 1). LPJ-GUESS lacks partitioning between direct and diffuse radiation, so there is no impact of enhanced diffuse radiation fertilization under SAI, which has been shown to play a role in global crop responses to SAI in process-based and statistical crop models (Clark et al., 2023; Fan et al., 2021; Proctor et al., 2018).

CLM5crop and pDSSAT both show that SAI benefits maize yield relative to climate change in nearly all areas of the world (Figure 3). While there are some regions where maize yield decreases in CLM5crop, such as parts of the United States and Russia, these decreases are not statistically significant (Figure 3). The largest increases to maize yield in CLM5crop under SAI are in areas that show the largest declines to yield under climate change, such as parts of Africa, India, and Southeast Asia (Figure 3). All significant changes to yield in CLM5crop and pDSSAT tend to be positive (Figure 3). There are strong yield declines in pDSSAT under SSP2-4.5 in major maize producing regions such as the central United States and eastern China (Figure 3). These maize yield declines under climate change are not entirely offset under SAI, meaning SAI would have little benefit to maize yield in these large producing regions (Figure 3). However, SAI causes maize yields to increase in parts of India, Africa, South America, and North America in pDSSAT relative to climate change (Figure 3). This causes the future negative impact to global maize yield in pDSSAT to be less severe under SAI than it is under climate change relative to the

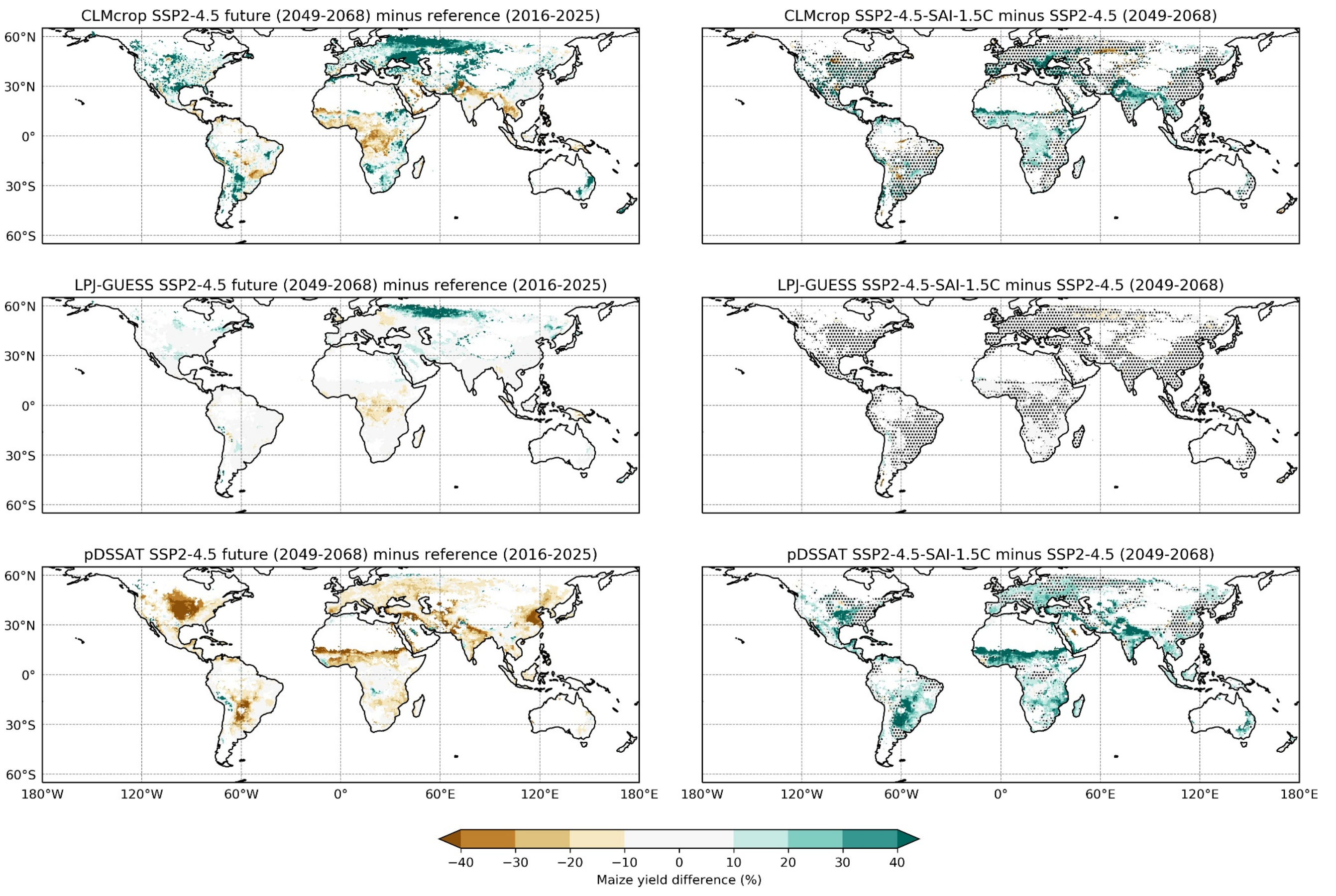

Figure 3. Relative maize yield difference between SSP2-4.5 future (2049–2068) minus reference (2016–2025) (left column) and SSP2-4.5-SAI-1.5C minus SSP2-4.5 averaged over the years 2049–2068 (right column). The left column plots correspond to the red lines and bars in Figures 1 and 2, and the right column plots correspond to the difference between the blue and red lines and bars in Figures 1 and 2. Stippled areas indicate grid cells where the difference is not statistically significant at the 95% confidence level based on a two-tailed Student's *t*-test.

reference period (Figure 2). LPJ-GUESS has essentially no significant changes to yield under SAI relative to climate change, which contrasts the results for CLM5crop and pDSSAT (Figure 3). There are slight decreases to maize yield under SAI in parts of Russia in LPJ-GUESS, but these changes are mostly insignificant (Figure 3). The variety of responses between models is likely due to the three models having varying sensitivity to temperature, with pDSSAT having the strongest sensitivity, CLM5crop having a moderate sensitivity, and LPJ-GUESS having a weak sensitivity (Clark et al., 2023; Müller et al., 2024). The importance of individual climate forcings under SAI was tested in CLMcrop in Clark et al. (2023), where temperature reduction under SAI was found to be the largest contributor to maize production changes. It is also possible that the reduction in total solar radiation under SAI negates any benefits from cooling in LPJ-GUESS, as LPJ-GUESS does not simulate diffuse radiation fertilization.

Although global maize production increases under SAI relative to climate change in pDSSAT, the changes under SAI are still a decrease of around 10% relative to the reference period over the years 2049–2068 (Figure 2). SAI would help to minimize the reduction in maize yield under SSP2-4.5 in CLM5crop and pDSSAT. LPJ-GUESS shows similar global production responses under both SAI and climate change (Figure 2). Crop models introduce greater uncertainty than climate models when estimating future agriculture yield due to their varying sensitivities to temperature, precipitation, and CO_2 concentration (Jägermeyr et al., 2021). This uncertainty remains true with SAI as well, with the three crop models used here showing a range of responses to future maize yield under both climate change and SAI. Since SAI would create an unprecedented environment for crops, existing crop models might not fully capture impacts from specific changes induced by SAI. Nevertheless, as a preliminary step, it is

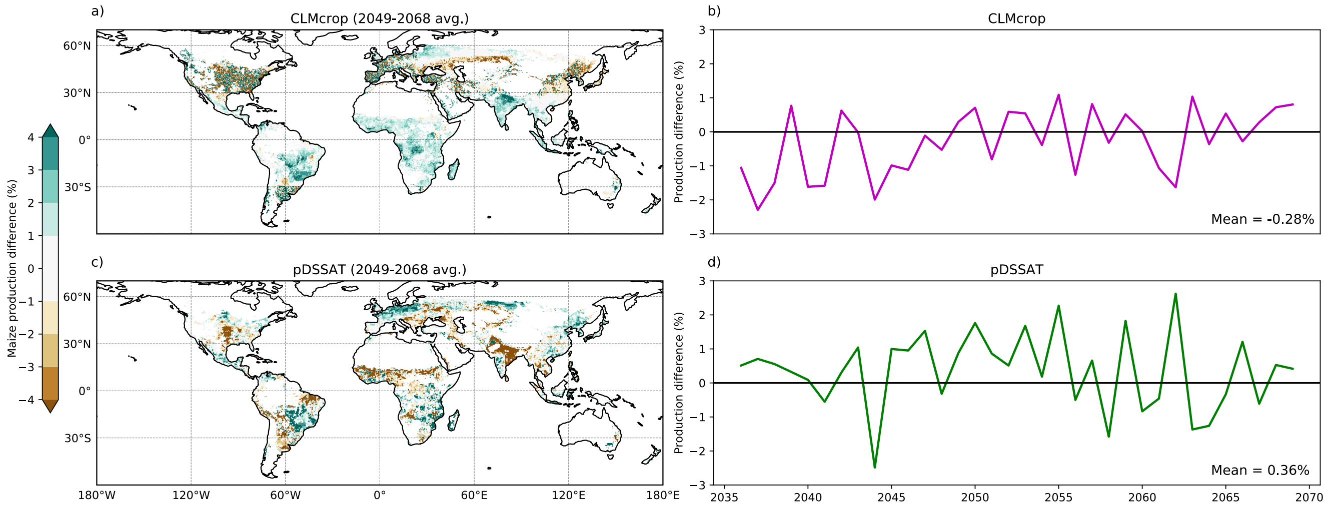

Figure 4. Maps of diffuse radiation impacts on global maize production in CLM5crop (a) and pDSSAT (c) over the years 2049–2068 and time series of diffuse radiation impacts on the sum of global maize production in CLM5crop (b) and pDSSAT (d) (SSP2-4.5-SAI-1.5C minus SSP2-4.5). For pDSSAT, this is calculated by comparing the differences between the SAI and climate change scenario with diffuse radiation data included and excluded. CLM5crop ran simulations that compared the impact of just changing the ratio of direct to diffuse radiation under SAI compared with the direct to diffuse ratio under climate change.

essential to simulate SAI's impact on agriculture using crop models, and this study serves as a pilot for a more comprehensive multi-crop, multi-climate model assessment.

3.2. Crop Model Responses to Changing Diffuse Radiation Under SAI

One of the key unique environmental changes resulting from SAI would be the modification of the quantity and partitioning of radiation reaching Earth's surface. SAI would reduce total incoming solar radiation and direct radiation, while increasing the fraction of diffuse light due to the scattering effect of the sulfate aerosols and changing cloud coverage. Decreasing total solar radiation tends to decrease plant photosynthesis, while increasing the diffuse fraction tends to increase photosynthesis by allowing more sunlight to reach leaves that are normally shaded (Roderick et al., 2001). This response has also been observed during volcanic eruptions, which are an analog for what could be expected from SAI (Gu et al., 2003).

It is not entirely clear which of these opposing mechanisms would dominate in the crop yield response. Proctor et al. (2018) used an empirical yield model based on observations of the 1991 Mount Pinatubo eruption to assess how SAI might impact global yield. They found an overall negative effect from the sulfate aerosols' impact on total radiation that roughly balanced benefits from cooling. However, the aerosols from the Pinatubo eruption were found to be more backscattering than that of other eruptions, such as El Chichón, and this backscattering is not necessarily seen in climate model simulations of SAI (Proctor et al., 2018). Proctor et al. (2018) also did not separate the effects of changing surface ozone and ultraviolet radiation, which could confound the results and make drawing comparisons more difficult, as current crop models do not account for changing surface ozone and ultraviolet radiation. Previous crop modeling studies of diffuse radiation impacts under SAI have tended to find positive impacts from enhanced diffuse radiation fertilization with negative impacts from reducing total solar radiation, with the overall effect being small (Clark et al., 2023; Fan et al., 2021). However, these studies used just one crop model and were forced by different scenarios. This variation in results between empirical and modeling studies means that further analysis with additional crop models is needed. Here we analyze impacts to maize from diffuse radiation fertilization under SAI using CLM5crop and pDSSAT (since LPJ-GUESS only considers total radiation).

Figure 4 shows the impact from diffuse radiation fertilization under SAI on global maize production in pDSSAT and CLM5crop. For pDSSAT, this is calculated by comparing the differences between the SAI and climate change scenario with diffuse radiation input data included and excluded. CLM5crop ran simulations that compared the impact of changing the ratio of direct to diffuse radiation under SAI compared with the direct to diffuse ratio under climate change. Under the ARISE-SAI scenario, the feedback control algorithm used to

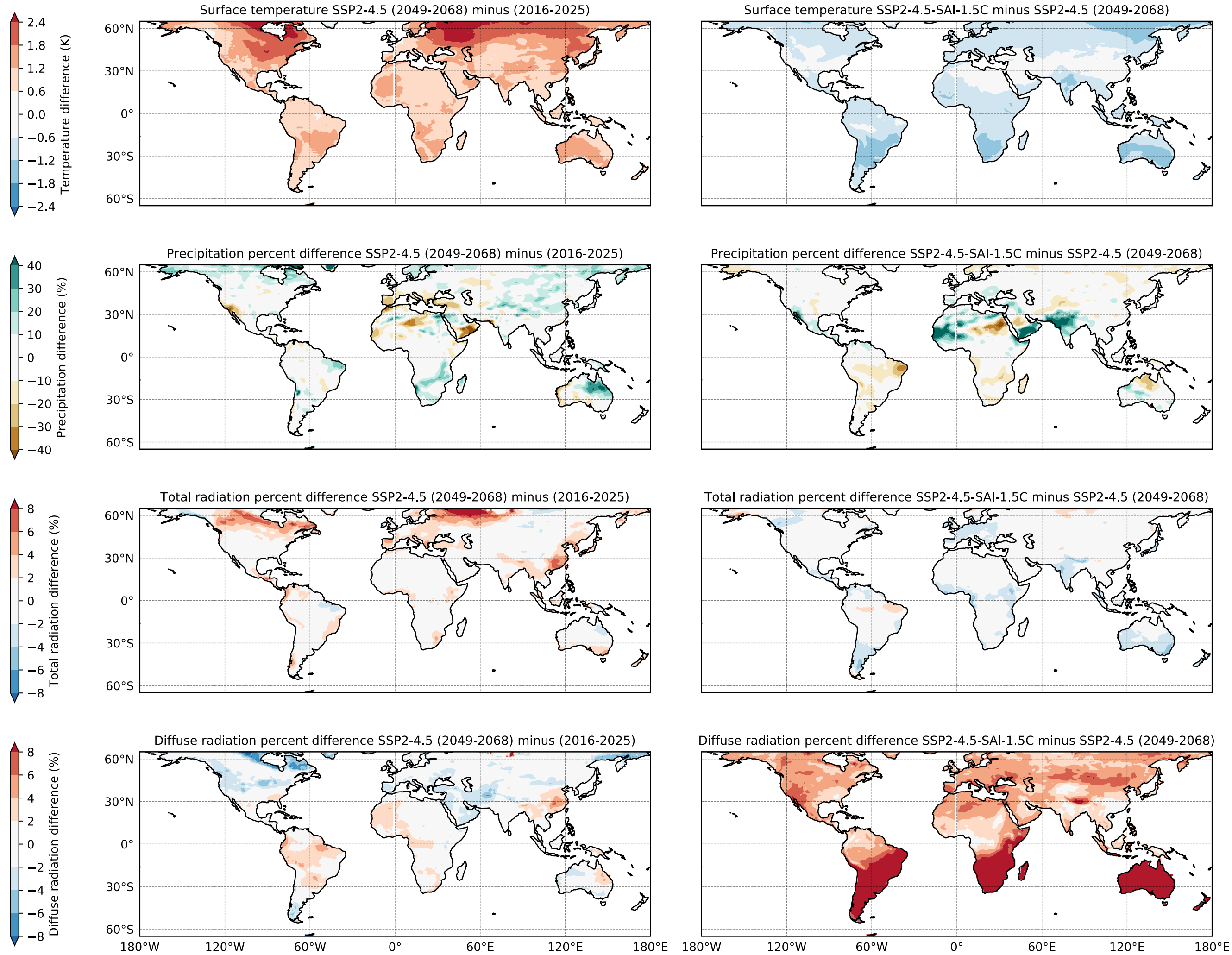

Figure 5. Maps of relative changes to temperature, precipitation, total radiation, and diffuse radiation under SSP2-4.5 future (2049–2068) minus SSP2-4.5 control (2016–2025) (left column) and SSP2-4.5-SAI-1.5C minus SSP2-4.5 (2049–2068) (right column) as simulated by CESM2-WACCM6 (Richter et al., 2022).

determine the amount and location of SO_2 injection places the majority of SO_2 injection in the Southern Hemisphere at 15°S (Richter et al., 2022), resulting in the enhancement of diffuse radiation from the injected aerosols being concentrated in the Southern Hemisphere (Figure 5). Since most maize is grown in the Northern Hemisphere, the impacts from diffuse radiation fertilization on global maize are muted under this scenario with the production changes within the range of natural variability seen in the reference period (Figure 1). There are even some years where production goes down from changing diffuse radiation, but this is likely due to cloud-related weather, natural climate variability, or changes in anthropogenic emissions of aerosols under the scenario SSP2-4.5 (Figures 4 and 5). This could be reduced in future studies by using additional ensemble members. Impacts to global maize production from diffuse radiation are small in both CLM5crop and pDSSAT, and vary between about −3% and +3%, with regional variations (Figure 4). In addition to most of the SO_2 injection taking place in the Southern Hemisphere, this SAI scenario also has a small temperature signal relative to other scenarios, like those used in Proctor et al. (2018) and Fan et al. (2021), as the SO_2 injection amount is small relative to these previous studies (Richter et al., 2022). We are relying on one climate model ensemble member to assess impacts from diffuse radiation, which is subject to substantial noise due to cloud-related weather. Most impacts to maize yield from diffuse radiation occurring in the Northern Hemisphere are subject to this noise, and the largest responses to yield are in the Southern Hemisphere where there are the largest changes to diffuse radiation (Figures 4 and 5). We expect that other climate models simulating the same SAI scenario with different SO_2 injection locations and amounts would show different diffuse radiation effects on crops (Henry et al., 2023).

Using additional climate models and crop models forced by different scenarios would help to reduce uncertainties.

4. Discussion

Despite the detailed process representation of the climate and crop models used in this study, the results are highly diverse. CESM2(WACCM6) showed a satisfactory ability to simulate past climate and was included in the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Danabasoglu et al., 2020). All three crop models have been tested substantially. pDSSAT contributed to the GGCMI Project Phase 3 simulations, which assessed impacts to global crop production under future climate change (Jägermeyr et al., 2021). LPJ-GUESS contributed to the GGCMI phase 2 simulations (Franke et al., 2020). All three crop models were evaluated together to test for their ability to simulate global and regional interannual yield variability in the GGCMI phase 1 evaluation (Müller et al., 2017). CLM5crop's ability to simulate past interannual changes to global and regional crop production has been tested in several other studies (Clark et al., 2023; Fan et al., 2021; Lombardozzi et al., 2020). Müller et al. (2017) and Clark et al. (2023) found that LPJ-GUESS, CLMcrop, and pDSSAT simulated historical global maize yield with a strong positive correlation with observations (Pearson correlation coefficient of 0.71, 0.89, and 0.91, respectively), supporting them for use in future projections. While all three crop models were evaluated against the same yield observation data set from the FAO, differences in the weather data sets used to force the models and differences in the spatial resolution of historical simulations could cause inconsistencies in model evaluation between studies. Evaluation of crop yields could be further hindered by inconsistencies in reported national yields and impacts from pest, disease, and agricultural practices not represented by the crop models. As LPJ-GUESS does not simulate diffuse radiation fertilization, it may miss the potential influence of diffuse radiation on crop production, which could be a factor to consider when interpreting LPJ-GUESS results for SAI scenarios. Besides the lack of representation of diffuse radiation in LPJ-GUESS, it is difficult to state that one model should be given a higher weight than another as each model has different strengths, weaknesses, and sources of uncertainty depending on their configuration and processes, which is why it is always best to use a multi-model ensemble (Martre et al., 2015).

While this study uses three crop models, it is limited by only using one ensemble member from one climate model and one SAI scenario. Using additional ensemble members in the future would provide more robust results by limiting noise due to natural climate variability. CESM2 is warm relative to observations, so using other climate models could help to reduce climate model uncertainty (Danabasoglu et al., 2020). Using bias correction in the future could also help to reduce any uncertainties introduced by the climate model but was not done in this study. While using three global crop models is an improvement upon past SAI impact studies, rigor would be increased by including additional models that feature the required process representations. Global gridded crop models show very large uncertainty of production impacts under future climate change, and crop model uncertainty is much larger than uncertainty stemming from climate models (Jägermeyr et al., 2021). This study serves as a first step for a more robust analysis of crop impacts from SAI, and more crop models and SAI scenarios are needed to simulate SAI impacts. It would also be beneficial to incorporate other impact models, such as fisheries models, to understand how food production will change both on land and in the ocean under SAI.

SAI would impact ultraviolet (UV) radiation and surface ozone, which are both important driving factors for crop production (NASEM, 2021). This study did not include the impacts on maize from changing UV radiation and surface ozone. While including surface ozone impacts in global processed-based crop models is a new area of model improvement, no global process-based crop model currently has the capability to simulate impacts from changing UV radiation. Improving the crop models and incorporating these impacts in future SAI crop modeling studies will be important to understanding the full story of how SAI would impact global crop production.

5. Conclusions

Placing sulfate aerosols in the stratosphere to maintain surface temperatures of 1.5°C above preindustrial levels caused maize production to increase by 0% in LPJ-GUESS, 4% in CLMcrop and 11% in pDSSAT over the years 2049–2068 under SSP2-4.5-SAI-1.5C relative to SSP2-4.5. CLM5crop and pDSSAT show benefits due to reduced heat stress under SAI, while LPJ-GUESS has a lower sensitivity to temperature and lacks representation of diffuse radiation fertilization, causing impacts under SAI and climate change to be globally very similar. CLM5crop and pDSSAT are less sensitive to other climate variables, like precipitation, and therefore the temperature impact dominated the overall response (Clark et al., 2023; Müller et al., 2024). CLMcrop and pDSSAT showed almost no areas of significant reduction of maize yield under SAI relative to climate change, and LPJ-GUESS showed no significant changes to maize yield anywhere in the world under SAI. pDSSAT had a large benefit to future maize production under SAI relative to climate change, CLM5crop had a moderate benefit, and LPJ-GUESS shows almost no difference between SAI and climate change. This model-dependent response to maize yield under SAI highlights remaining uncertainty in the global temperature response of maize production under both future climate change and possible SAI implementation. In the scenario and models we used, enhanced diffuse fertilization has a very small impact on global maize production. Using multiple climate models which can produce diffuse radiation output and multiple crop models which can simulate diffuse radiation fertilization effects could help to further constrain remaining uncertainties in the process-based crop model response to changing radiation under SAI. Improving model development and utilizing additional crop models, climate models, and SAI scenarios will be necessary to better understand possible impacts to maize production and inform future policy decisions, and there is no clear answer yet as to how global maize may be impacted by SAI.

Data Availability Statement

Climate model output from SSP2-4.5 and ARISE-SAI-1.5C is available in Mills et al. (2022). Crop model output analyzed here is available at figshare.com (Clark et al., 2024). All scripts used for processing the data in this analysis and generating figures are available at zenodo.org (Clark, 2024).

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