



# Soil organic carbon improvement for mitigating crop yield losses under global warming

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## ABSTRACT

Rising temperatures pose a significant threat to crop production worldwide. While many studies have examined the effects of warming on crop yields, the role of soils in crop-climate interactions is often overlooked. This study investigates how soil properties influence crop yield responses to increased growing season temperatures, using an ensemble of nine global gridded crop models and 37 CMIP6 climate models under three shared socio-economic pathway scenarios. Our findings show that, during 1980–2010, a 1°C increase in temperature resulted in yield changes of –2.3 % for maize and +3.0 % for soybean. However, under future climate scenarios of 2050–2080, yields are projected to decline by –6.6 % to –7.5 % for maize and –8.9 % to –10.7 % for soybean. Soil properties account for 51 % and 59 % of the spatial variations in temperature sensitivity for global maize and soybean yields, respectively, with soil organic carbon (SOC) emerging as the most influential factor. Improving SOC through farming and soil conservation practices is expected to reduce warming-induced yield losses by 0.5–1.1 % °C<sup>–1</sup> for maize and 1.3–2.5 % °C<sup>–1</sup> for soybean, particularly in dryland areas. These benefits diminish under more extreme warming scenarios (i.e., SSP585 vs. SSP126), but can be amplified by adopting new crop varieties with fixed growing seasons. Our findings highlight the buffering effects of SOC on crop responses to warming, suggesting a promising soil-based solution for building resilience in global food production under climate change.

## 1. Introduction

With the global population projected to plateau at around 9 billion by mid-century, food production may need to increase by 59 % to as

much as 98 % to meet the rising demand (Godfray et al., 2010; Harrison and Liu, 2024; Seppelt et al., 2022). Despite continuing technological and agronomic improvements, efforts to increase crop production are now more jeopardized by climate change than ever before in many

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world regions (Harrison, 2021; Su et al., 2021). Temperature shifts, altered precipitation patterns, and rising atmospheric CO<sub>2</sub> levels are the primary drivers of yield fluctuations under climate change (Shi et al., 2022). Rising temperatures are likely to intensify heat and drought stress, accelerate crop phenology, disrupt planting and harvesting schedules, and reduce water availability during critical cropping periods (Muleke et al., 2022; Zhu et al., 2022a). Extreme rainfall and drought events can also higher the risk of crop failure (Fu et al., 2023; Liu et al., 2023), and the variations in temperature, precipitation or their interaction were found to account for roughly one-third of global crop yield variability (Ray et al., 2015). Therefore, understanding the impacts of changing climatic factors on crop yields is essential for developing strategies to ensure food security.

Process-based crop models are widely used to project crop yields, and the Global Gridded Crop Model Intercomparison (GGCMI) of the Agricultural Model Intercomparison and Improvement Project (AgMIP) provides essential data products for analyzing crop yield responses to climate change at global scales (Elliott et al., 2015; Jägermeyr et al., 2021; Li et al., 2023a; Müller et al., 2017). However, the understanding of how soil properties impact crop yield responses to climate in these models remain incomplete. Beyond serving structural supports, soil properties directly influence the retention and release of water and nutrients essential for crop growth (Andrade et al., 2024; Cordeiro et al., 2022). High-quality soils (with medium-textured and high soil organic matter) were found to reduce the sensitivity of crop production to climate variability and improve yield stability (Qiao et al., 2022). Soil organic carbon (SOC), a ‘master’ indicator of soil health, is expected to play a vital role in mitigating and adapting to the adverse effects of climate warming (Deng et al., 2023; Droste et al., 2020; Feng et al., 2022; Luo et al., 2023; Teng et al., 2024). In addition, a recent study reported that yields of corn, soybean, cotton, and barley are most sensitive to warming in coarse-textured soils compared to medium- and fine-textured soils in the United States (Huang et al., 2021). Clay soils are often characterized by a high water-holding capacity, while coarse-textured soils tend to have higher rates of nitrogen mineralization (Mäkinen et al., 2017; Soinne et al., 2020). These differences in soil properties are likely to result in soil-dependent responses of crop yields under climate change.

Maize is widely cultivated in low-latitude regions, which are projected to face the most severe climate change impacts due to their proximity to critical temperature thresholds (Jägermeyr et al., 2021; Tigchelaar et al., 2018; Zabel et al., 2021). Several studies have explored the buffering effects of soils on maize yield responses to historical climate perturbations (Chen et al., 2024; Deng et al., 2020; Feng et al., 2022). While the elevated atmospheric carbon dioxide associated with climate change has rarely been considered. As a C4 crop, maize has limited capacity to benefit from elevated [CO<sub>2</sub>] (Kimball, 2016); conversely, elevated [CO<sub>2</sub>] directly stimulates C3 photosynthesis, making the so-called [CO<sub>2</sub>] fertilization effect more likely to offset a portion of climate-induced yield losses in C3 crops like soybean (Jin et al., 2017). Moreover, C4 photosynthesis has greater carbon gain than C3 under conditions of low [CO<sub>2</sub>] and high temperatures, whereas more carbon gain in C3 than C4 plants under high [CO<sub>2</sub>] and cool temperatures; and water availability also impacts C3 and C4 differently, either independently or in concert with changes in temperature and [CO<sub>2</sub>] (Zhou et al., 2018). Given these varied responses of different crops to climate factors, the contribution of soil properties to crop yield is likely to differ across crop types.

Although the negative impacts of climate change on crop yields are widely recognized, actual yield responses to temperature increase vary significantly across regions (Asseng et al., 2015). Moreover, previous meta-analyses have shown that yield gains through conservation agriculture practices are often observed in arid regions, where improved soil structure is particularly beneficial (Pittelkow et al., 2015; Su et al., 2021). Thus, we hypothesize that spatial variation in soil properties contributes to these region-specific yield responses under global

warming, and soil quality enhancement can reduce yield temperature sensitivity more effectively in dryland than in non-dryland areas. To test this hypothesis, we developed a yield-climate relationship at a global grid scale using a multiple regression model across two periods: the historical period (1980–2010) and a future period (2050–2080) under three shared socio-economic pathways scenarios (SSP126, SSP245, and SSP585). We then quantified the temperature sensitivity of maize and soybean yields, and applied a random forest model to assess the contribution of soil properties on the temperature sensitivity. Finally, we proposed SOC improvements to reduce yield temperature sensitivity under future climate scenarios, and compared these benefits between current and future varieties and between dryland and non-dryland regions. We aimed to answer the following questions: (1) What are the spatial patterns of global warming impacts on maize and soybean yields? (2) How do soil properties modulate the temperature sensitivity of these crop yields? Our goal is to provide insights into potential soil-based strategies for future climate change adaptation and mitigation to safeguard food production.

## 2. Materials and methods

### 2.1. GGCM emulators

The GGCM emulators based on Global Gridded Crop Model Intercomparison (GGCMI) Phase 2 simulation were developed by Franke et al. (2020b). The GGCMI Phase 2 experiment compared crop model simulations under uniform perturbations in carbon, temperature, water, nitrogen levels and adaptation to shifting growing seasons (CTWN-A) (Franke et al., 2020a), which produced a structured training dataset for statistical emulation. By fitting individual regression models for each crop, model, and pixel to the regressors of the CTWN-A analysis, the emulators provide a tool that can effectively capture crop yield response for different climate scenarios. Such emulators combine the advantages of both process-based crop models and statistical models, and have been applied successfully for reproducing crop yields under climate model projections (Li et al., 2023a, 2023b; Zabel et al., 2021).

We employed emulators to simulate maize and soybean yields at a grid scale (0.5° resolution) using atmospheric CO<sub>2</sub>, changes in growing-season temperatures (ΔT) and precipitation (ΔP), and applied nitrogen. Separate emulations were conducted for rainfed and irrigated yields, both with no crop adaptation (existing varieties) and with adaptation (future varieties). To focus on yield changes under climate change, the rainfed and irrigated yields were aggregated for analysis using crop area data from Monfreda et al. (2008). A total of nine GGCMs (CARAIB, EPIC-TAMU, JULES, GEPIC, LPJ-GUESS, LPJmL, pDSSAT, PEPIC, and PROMET) were used for maize, and eight GGCMs (excluding LPJ-GUESS) were available for soybean. Given that some GGCMs tend to differ in their baseline crop productivity levels, we harmonized simulated crop yields to match observed yield patterns, following Müller et al. (2021) and Li et al. (2023b):

$$Y_{i,j} = Y_{sim,i,j} \times \frac{Y_{obs,t,j}}{Y_{sim,t,j}} \quad (1)$$

where  $Y_{i,j}$  and  $Y_{sim,i,j}$  are the crop yields of the year  $i$  in grid cell  $j$  after and before correction, respectively.  $Y_{obs,t,j}$  and  $Y_{sim,t,j}$  are the average values of observed and simulated yields during the historical period  $t$  (1980–2010 in this study) in grid cell  $j$ .

### 2.2. Climate and soil data

Monthly temperature and precipitation data from simulations of 37 general circulation models (GCMs) across three Shared Socioeconomic Pathways (SSP126, SSP245 and SSP585) were used to drive the GGCM emulators (Table S1). The GCM data, sourced from the CMIP6 archives (<https://aims2.llnl.gov/search/cmip6/>), were resampled to a 0.5°

resolution. The mean temperature and total precipitation during the growing season of maize and soybean were calculated as weighted averages of the monthly climate data. Thus, yield changes under different SSP scenarios were attributed to changes in temperature, precipitation, and  $[CO_2]$  levels.

Gridded soil data were derived from the Harmonized World Soil Database (HWSD version 1.2) (Wieder et al., 2014). The mapping raster of the HWSD was aggregated from its native resolution of 30 arc-second to a 0.5° resolution for complying with the GCMs. The HWSD combines regional and national updates of soil characteristics worldwide, making it available for global analyses. Soil properties were selected if they were model parameters so that their impacts can be captured by modeling methods; their characteristics did not change greatly under conventional farming management practices; and they were commonly available in gridded soil datasets (Feng et al., 2022). Finally, five key soil properties at 0–30 cm depth, including soil organic carbon ( $kg\ C\ m^{-2}$ ), bulk density ( $g\ cm^{-3}$ ), clay content (%), sand content (%) and pH, were extracted for maize and soybean croplands.

### 2.3. Temperature sensitivity of crop yield

Temperature sensitivity of maize and soybean yields was estimated using a panel data model, following the approach of previous studies (Deng et al., 2020; Feng et al., 2022; Zhu et al., 2019). Growing-season temperature changes ( $T$ , °C), growing-season precipitation changes ( $P$ , %), and atmospheric  $CO_2$  concentrations ( $[CO_2]$ , ppm) were used as explanatory variables:

$$\ln(Y_{ij}) = \beta_1 T_{ij} + \beta_2 T_{ij}^2 + \beta_3 P_{ij} + \beta_4 P_{ij}^2 + \beta_5 [CO_2]_{ij} + \beta_6 [CO_2]_{ij}^2 + \varepsilon \quad (2)$$

where  $\ln(Y_{ij})$  is the natural logarithm of crop yields of the year  $i$  in grid cell  $j$ . The quadratic terms of  $T$ ,  $P$ , and  $[CO_2]$  simulate the nonlinear response of yield to temperature, precipitation, and  $CO_2$  changes, respectively.  $\beta_1$  to  $\beta_6$  are regression coefficients, and  $\varepsilon$  is the model error.

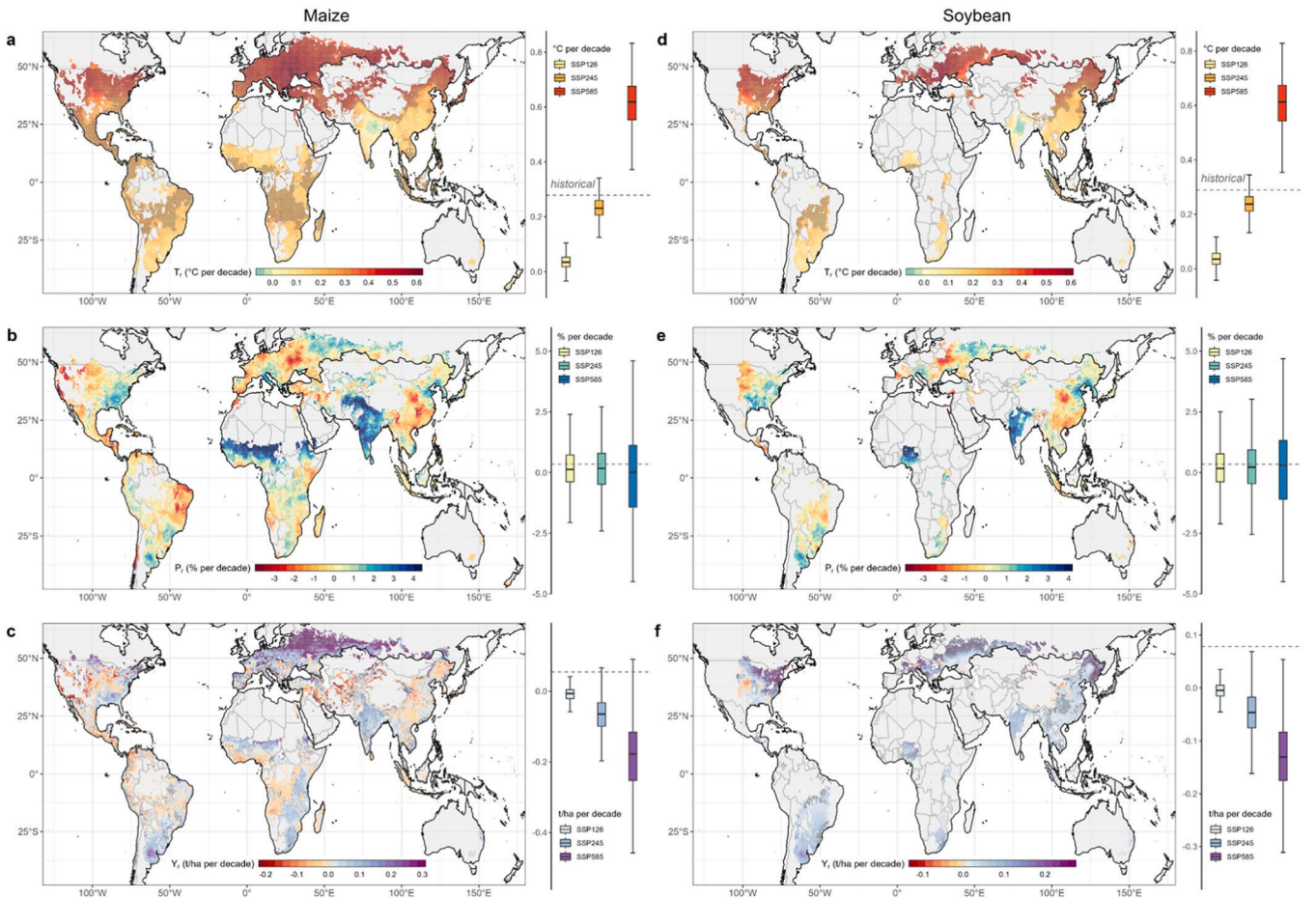
Then, the temperature sensitivity of crop yields, indicating the percentage of yield change per 1°C warming, was computed as the partial derivative of yield with respect to temperature:

$$S_{Y,T} = \frac{\partial Y}{\partial T} \times 100\% = (\beta_1 + 2\beta_2 \bar{T}_{ij}) \times 100\% \quad (3)$$

where  $\bar{T}_{ij}$  is the average temperature during period  $t$  (1980–2010 for historical period and 2050–2080 for future period) in grid cell  $j$ .  $\beta_1$  and  $\beta_2$  are regression coefficients derived from Eq. (2).  $S_{Y,T}$  denotes temperature sensitivity, with positive values indicating yield increase and negative values indicating yield decrease with warming. Yield sensitivity to precipitation was excluded due to no significant precipitation trends observed in most cropping areas (Fig. 1b, e).

### 2.4. Relationship between temperature sensitivity and soil properties

We used a random forest (RF) model to evaluate the non-linear relationship between temperature sensitivity and soil properties. RF is an ensemble learning method that leverages multiple decision trees for



**Fig. 1.** Linear trends in growing-season mean temperature ( $T$ ), precipitation ( $P$ ), and crop yield ( $Y$ ) for maize (a–c) and soybean (d–f). Global maps depict the median values derived from 37 general circulation models (GCMs) for the historical period 1980–2010. Boxplots represent future projections for the period 2050–2080 under three shared socioeconomic pathway scenarios (SSP126, SSP245, and SSP585). Stippling on the maps marks regions where more than half of the 37 GCMs exhibit statistically significant trends ( $p < 0.05$ ).



prediction (Breiman, 2001). In addition to being faster and easier to train, RF also has advantages to reduce overfitting problems and improve model accuracy. We built the RF model using the ‘Ranger’ package in R, with crop yield temperature sensitivity as the dependent variable and five soil properties as independent variables. Model performance was assessed using the coefficient of determination ( $R^2$ , estimated using the internal out-of-bag samples) and the index of agreement (IA, a standardized measure of the degree of model prediction error, with value varies between 0 and 1, where a value of 1 indicates a perfect match and a value of 0 indicates no agreement at all) (Willmott, 1981). Key soil properties were determined by the variable importance which is interpreted as the increase in the mean square error ( $IncMSE$ , %) due to the random permutation of that variable in RF. The greater the increase in error, the more important the variable is.

Separate RF models were built for maize ( $n = 22,650$ ) and soybean ( $n = 10,631$ ). For potential SOC improvement in the future, we used the medium-scenario data from Zomer et al. (2017). The dataset provided a spatially articulated estimate of the SOC distribution and increases in the top 30 cm of soils over 20 years on all available cropland, achieved through soil conservation practices like cover cropping, mulching, conservation tillage, and organic manure application. We replaced the original SOC input with the improved one in RF models to predict changes in temperature sensitivity induced by SOC increases across future climate scenarios. Since the aridity index (AI), defined as the ratio of mean annual precipitation to potential evapotranspiration, is an effective measure of long-term climate conditions, we calculated the AI for the historical period of 1980–2010 at the grid scale to identify dryland ( $AI \leq 0.65$ ) and non-dryland ( $AI > 0.65$ ) regions in this study (Trabucco and Zomer, 2018).

### 3. Results

#### 3.1. Climate and yield trends

Significant trends in the temperature of crop growing season were observed during the historical period (1980–2010), with average increases of  $0.28^\circ\text{C}$  per decade for maize (66 % of grids showing significant trends) and  $0.29^\circ\text{C}$  per decade for soybean (60 % of grids showing significant trends). Large cropping areas of North America, Europe, Russia and northeast China experienced above-average positive trends in growing-season temperature (Fig. 1a, d). For the future period (2050–2080), projected average increase rates of temperature per decade were  $0.037^\circ\text{C}$ ,  $0.23^\circ\text{C}$ , and  $0.61^\circ\text{C}$  for maize, and  $0.036^\circ\text{C}$ ,  $0.24^\circ\text{C}$ , and  $0.61^\circ\text{C}$  for soybean, under SSP126, SSP245, and SSP585, respectively. However, no significant trends were detected in total growing-season precipitation across most cropping areas during the historical period, and precipitation projections for the future period varied widely (Fig. 1b, e).

For crop yields, maize showed a general increase in mid- to high-latitude regions of the Northern Hemisphere, with Russia exhibiting a respectively strong trend of  $0.20 \text{ t ha}^{-1}$  per decade, and 50 % of grids showing statistically significant increases during the historical period (Fig. 1c). In contrast, most grids in the central United States and Central Asia displayed negative yield trends. Under future climate scenarios, the projected average maize yield trends were  $-0.01 \text{ t ha}^{-1}$ ,  $-0.07 \text{ t ha}^{-1}$ , and  $-0.19 \text{ t ha}^{-1}$  per decade under SSP126, SSP245, and SSP585, respectively — all lower than the historical trend of  $0.05 \text{ t ha}^{-1}$  per decade. For soybean, more positive yield trends were observed during the historical period, particularly in the mid-west United States, Europe, and northeast China, with a global average increase of  $0.08 \text{ t ha}^{-1}$  per decade (Fig. 1f). However, future projections indicated declining yield trends for soybean, with rates of  $-0.01 \text{ t ha}^{-1}$ ,  $-0.05 \text{ t ha}^{-1}$ , and  $-0.13 \text{ t ha}^{-1}$  per decade under SSP126, SSP245, and SSP585 scenarios, respectively.

#### 3.2. Temperature sensitivity of crop yields

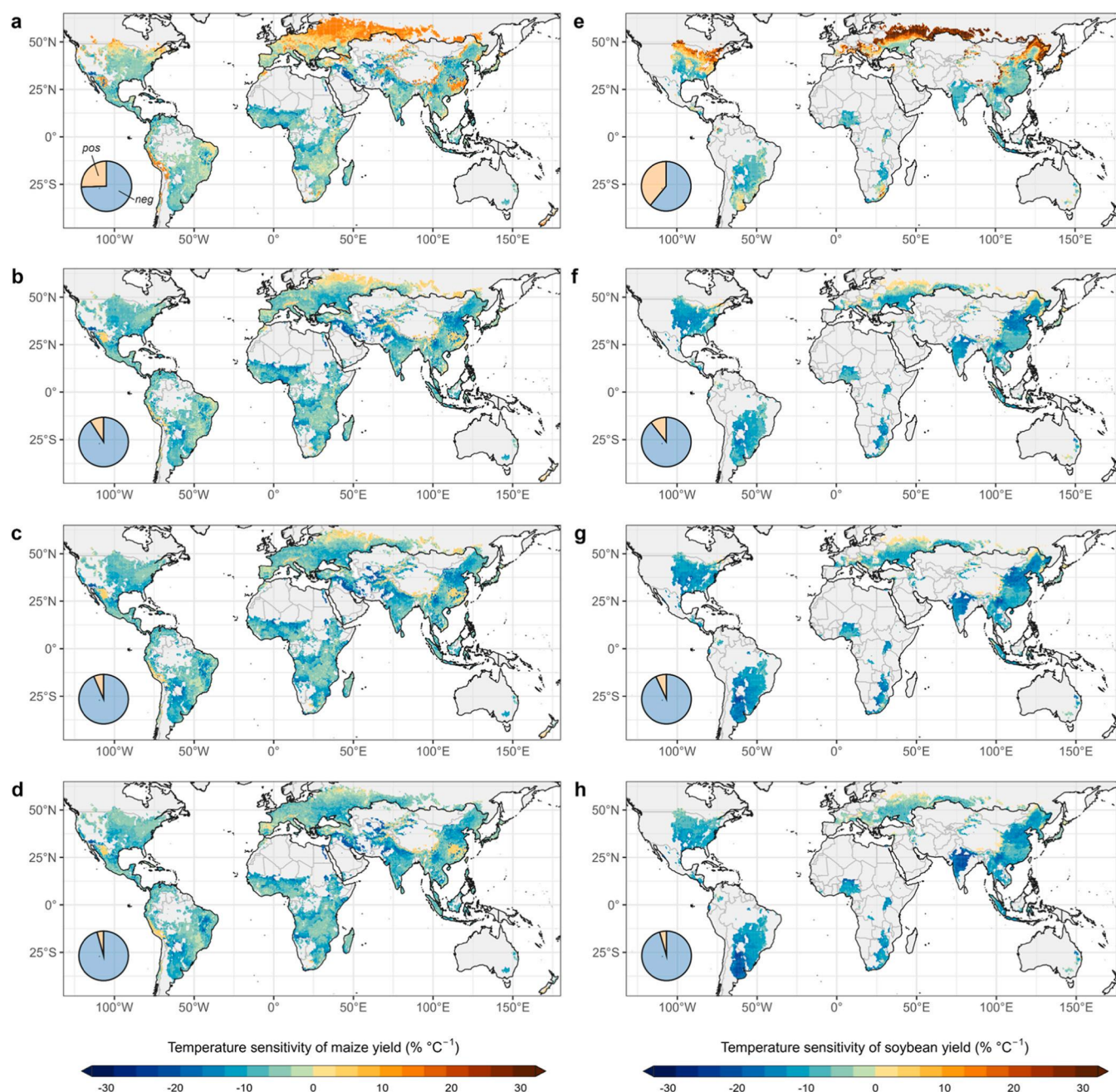
Globally, maize yield responses to warming averaged  $-2.3 \% ^\circ\text{C}^{-1}$  during the historical period, with 26 % of grids showing positive values. Under future climate scenarios, maize yield temperature sensitivity declined further, averaging  $-6.6 \% ^\circ\text{C}^{-1}$  under SSP126 (9 % positive grids),  $-7.4 \% ^\circ\text{C}^{-1}$  under SSP245 (6 % positive grids), and  $-7.5 \% ^\circ\text{C}^{-1}$  under SSP585 (4 % positive grids) (Fig. 2a–d). Soybean yields responded positively to warming during the historical period, with an average temperature sensitivity of  $3.0 \% ^\circ\text{C}^{-1}$  (39 % positive grids). However, under future climate scenarios, soybean yield responses became increasingly negative, with sensitivities averaging  $-8.9 \% ^\circ\text{C}^{-1}$  under SSP126 (10 % positive grids),  $-10.2 \% ^\circ\text{C}^{-1}$  under SSP245 (7 % positive grids), and  $-10.7 \% ^\circ\text{C}^{-1}$  under SSP585 (5 % positive grids) (Fig. 2e–h). While some northern high-latitude cropping regions exhibited enhanced yield responses to warming, these areas also had high coefficients of variation, reflecting significant uncertainty in model predictions (Fig. S1). Moreover, uncertainty in the  $\text{CO}_2$  effects contributed to much overall model uncertainty, with greater impacts on soybean yield predictions compared to maize. Soybean yield predictions displayed the greatest losses in the main-producer regions – the United States and Brazil – paired with large gains across parts of China and other high-latitude regions (Fig. S2).

#### 3.3. Contribution of soil properties to yield temperature sensitivity

The Random Forest (RF) models explained 51 % and 59 % of the variation in yield temperature sensitivity for maize and soybean, respectively, with high indices of agreement (0.86 for maize and 0.88 for soybean) during the historical period (Fig. 3a, c). This suggests that the spatially heterogeneous temperature sensitivity of both crops is largely driven by soil heterogeneity, including factors such as SOC, bulk density, pH, clay and sand content. Among these variables, SOC emerged as the most important variable, with importance values ranging from 25 % to 28 % for maize and 26–28 % for soybean (Fig. 3b, d). Increasing SOC content notably reduced the negative impact of temperature on crop yields when SOC levels were below approximately  $13 \text{ kg C m}^{-2}$  (Fig. S3 a, f). Current global SOC levels remain low (Fig. S4 a), suggesting significant potential for global soils to increase SOC before reaching the optimal threshold, beyond which further increases in SOC generate no additional mitigation in temperature sensitivity. Sand and clay content also played critical roles, with relative importance values ranging from 17 % to 28 % (Fig. 3b, d). The impact of sand content on temperature sensitivity followed a hump-shaped pattern, with increasing sand content initially weakening the negative temperature sensitivity before intensifying it (Fig. S3 c, h). In contrast, increasing clay content led to greater yield losses per  $1^\circ\text{C}$  increase in temperature before leveling off (Fig. S3 b, g).

#### 3.4. Impact of SOC improvement on yield temperature sensitivity

The temperature sensitivity of maize and soybean yields was projected to benefit from increased SOC through improved farming and soil conservation practices, regardless of future climate scenarios (Figs. 4 and 5). At the continental scale, the reduction in maize yield losses due to warming was most pronounced in Africa, where SOC improvement mitigated yield losses by  $1.3 \% ^\circ\text{C}^{-1}$ , followed by North America ( $1.2 \% ^\circ\text{C}^{-1}$ ) and South America ( $1.0 \% ^\circ\text{C}^{-1}$ ), all surpassing the global average of  $0.9 \% ^\circ\text{C}^{-1}$  under SSP126 with current crop varieties. However, these benefits diminished under more extreme warming scenarios (i.e., SSP585 compared to SSP126) but could be amplified by adopting new crop varieties (Fig. 4). For soybean, SOC improvement significantly alleviated widespread warming-induced yield losses, particularly in the major production regions like North America and South America. In these regions, SOC improvement avoided 1.4–4.9 % and 2.1–4.2 % of yield losses per  $1^\circ\text{C}$  warming with current and future crop varieties,



**Fig. 2.** Spatial pattern of temperature sensitivity for maize yield (a–d) and soybean yield (e–h). Maps show median values of temperature sensitivity derived from 37 general circulation models (GCMs) for the historical period 1980–2010 (a, e), and for future projections during 2050–2080 under SSP126 (b, f), SSP245 (c, g), and SSP585 (d, h). Pie charts inserted within each map indicate the percentage of grids with positive or negative temperature sensitivities.

respectively (Fig. 5).

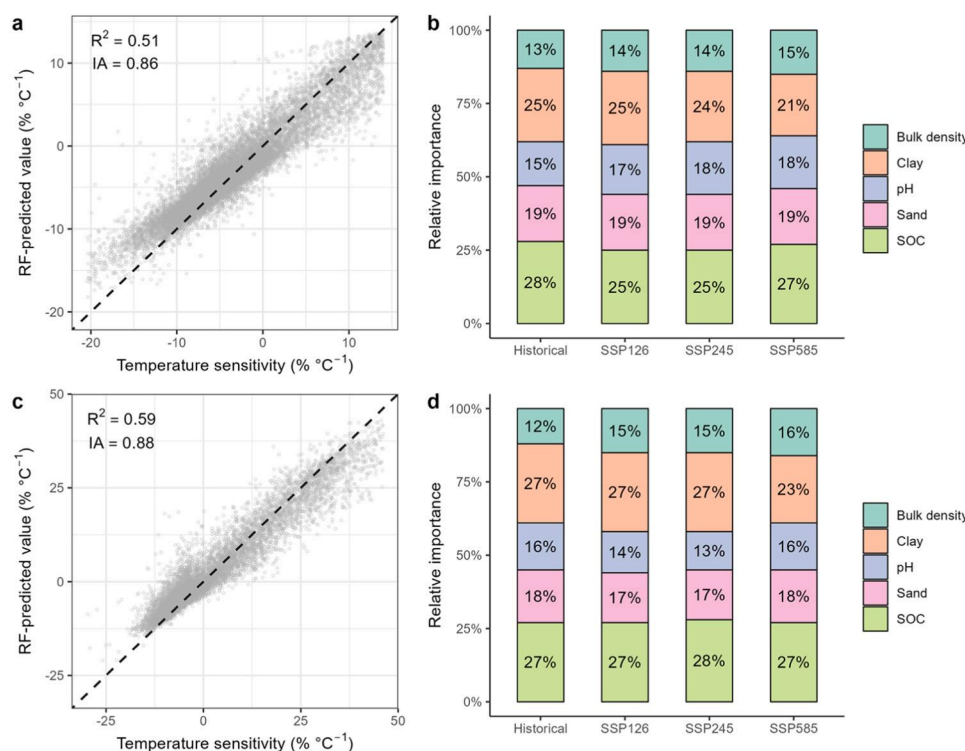
Under future climate conditions, the reduction in maize yield losses due to warming was more pronounced in dryland regions with SOC improvement, while adopting new crop varieties was more effective in mitigating yield losses in non-dryland regions (Fig. 6a). For example, SOC improvement increased maize yield temperature sensitivity by averages of 1.2–1.9 % °C<sup>-1</sup> across different scenarios in dryland regions, but the changes were negligible in non-dryland regions. For soybean, the positive impact of SOC improvement on yield temperature sensitivity was comparable between dryland and non-dryland regions (1.7–2.8 % °C<sup>-1</sup> versus 1.1–2.4 % °C<sup>-1</sup>), as well as between current and new crop varieties (1.1–2.7 % °C<sup>-1</sup> versus 1.4–2.8 % °C<sup>-1</sup>) (Fig. 6b).

## 4. Discussion

### 4.1. Crop yield response to rising temperatures

Consistent with previous studies, our findings indicate that future warming climate will substantially reduce maize and soybean yields, particularly under the SSP585 scenario, with impacts varying across regions (Li et al., 2023b; Rose et al., 2016; Rosenzweig et al., 2013). During the historical period (1980–2010), rising temperatures enhanced maize and soybean yields at mid to high latitudes, such as Eastern Europe, Russia, and northeastern China (Fig. 2a, e). In these regions, temperatures were below crop optimal levels, and warming extended the growing season, leading to positive yield impacts, consistent with findings by Iizumi et al. (2017) and Lin et al. (2021). However, under





**Fig. 3.** Comparison of temperature sensitivity and random forest (RF) model predictions across global grids for maize (a) and soybean (c) during the historical period (1980–2010), along with the relative importance of soil properties based on model outputs (b for maize and d for soybean). The dashed line represents the 1:1 ratio line.

future scenarios (2050–2080), warming predominantly had adverse effects on yields for both crops across most regions, with hotspots in areas already experiencing high-temperature stress, such as India and Brazil (Fig. 2b–d, f–h), as reported by Teixeira et al. (2013). Generally, the negative impacts of warming were more pronounced for soybean than maize in the tropics, likely due to the lower optimal leaf temperature for photosynthesis of soybean (Lin et al., 2021; Lobell and Gourdji, 2012). Additionally, higher temperatures after the mid-century will shorten growing season length and increase water demand through greater evaporation, which cannot be mitigated fully by CO<sub>2</sub> fertilization effects (Harrison et al., 2014; Muleke et al., 2022; Rosenzweig et al., 2013).

The slightly lower negative temperature sensitivity of maize yields compared to soybean in future scenarios can also be attributed partially to the higher proportion of irrigated maize areas (17.8 %) relative to soybean (9.5 %). Rising temperatures increase atmospheric water demand, leading to drought stress through elevated vapor pressure deficit, which can be alleviated by irrigation (Elliott et al., 2014; Lesk et al., 2021; Lobell et al., 2014). Furthermore, adopting future crop varieties will become increasingly important to preserve yields under future climate forcing scenarios (Figs. 4 and 5). The GGCMi assumed that future cultivars were modified to maintain their original growing season length under each temperature scenario (Franke et al., 2020a). By incorporating traits such as delayed maturity and improved heat tolerance, breeding programs can develop crop varieties better equipped to withstand the adverse effects of rising temperatures (Asseng et al., 2019; Tao et al., 2022; Zabel et al., 2021).

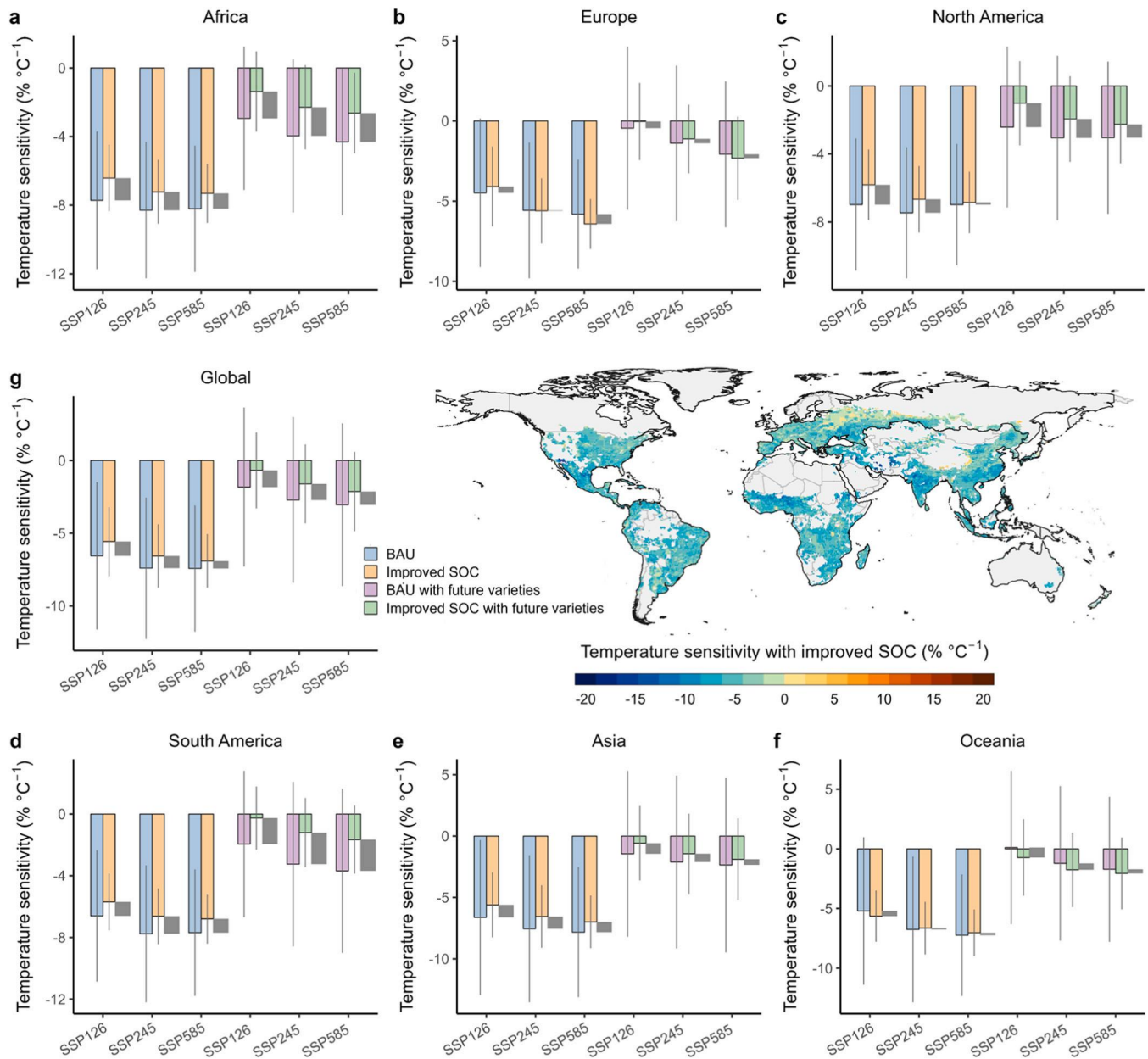
#### 4.2. SOC contribution to mitigate warming-induced yield losses

Our findings highlight the important role of soil in mitigating crop yield losses and enhancing system resilience to future warming climates on a global scale. As a fundamental component of the soil-plant-atmosphere continuum, soil can influence crop-climate interactions, as reported by Feng et al. (2022) and Chen et al. (2024). In our analysis,

soil properties explained a large share of the variation in crop yield temperature sensitivity, with SOC identified as the most influential factor (Fig. 3). SOC contributes to multiple soil-based ecosystem services (Lal, 2016). For example, SOC enhances plant-available water by increasing soil porosity (Huang et al., 2021), improves nutrient cycling and availability through SOC mineralization (Moinet et al., 2023), supports nutrient retention via increased cation exchange capacity (Jian et al., 2020), and provides habitat for beneficial soil microbiota. These mechanisms collectively bolster soil health and favor crop growth, even under the stress of a warming climate (Teng et al., 2024). Moreover, soils rich in organic carbon exhibit greater resilience to adverse weather conditions, buffering against the impacts of climate extremes on crop production (Droste et al., 2020), thereby reducing yield sensitivity to temperature.

Based on the observed relationship between temperature sensitivity and SOC (Fig. S3 a, f), our analysis suggested that declines in crop yields due to warming could be mitigated through SOC improvement. This finding aligns with results from field experiments (Ma et al., 2023), data-driven approaches (Deng et al., 2023), meta-analyses (Oldfield et al., 2019) and crop modeling studies (Feng et al., 2022). Current SOC content in most maize and soybean croplands remained below 8 kg C m<sup>-2</sup> (Fig. S4), highlighting substantial potential for stabilizing crop yields under warming conditions through SOC enhancement. Our results also indicated that improving SOC had a greater positive impact on crop yields in dryland areas compared to non-dryland regions (Fig. 6). This can also be attributed to the ability of SOC to enhance soil water retention, which is particularly beneficial in water-scarce regions. Conversely, in wetter regions with consistently saturated soils or high-water tables, especially in poorly drained areas, increased soil water retention from SOC improvement may lead to unfavorable conditions for crop growth (Huang et al., 2021).

Beyond SOC, soil sand and clay content also played a significant role in modulating crop yield sensitivity to temperature (Fig. 3). Zhu et al. (2022b) demonstrated that soils with higher sand content provided



**Fig. 4.** Improved SOC-induced temperature sensitivity changes for maize. The central map shows temperature sensitivity with improved SOC during 2050–2080 under SSP126. Each bar chart shows the mean values of temperature sensitivity under different scenarios globally and across six continents: Africa (a), Europe (b), North America (c), South America (d), Asia (e), and Oceania (f) and globally (g). Error bars indicate standard deviations, and gray bars show the changes induced by improved SOC under each scenario. BAU means scenario with no SOC improvement.

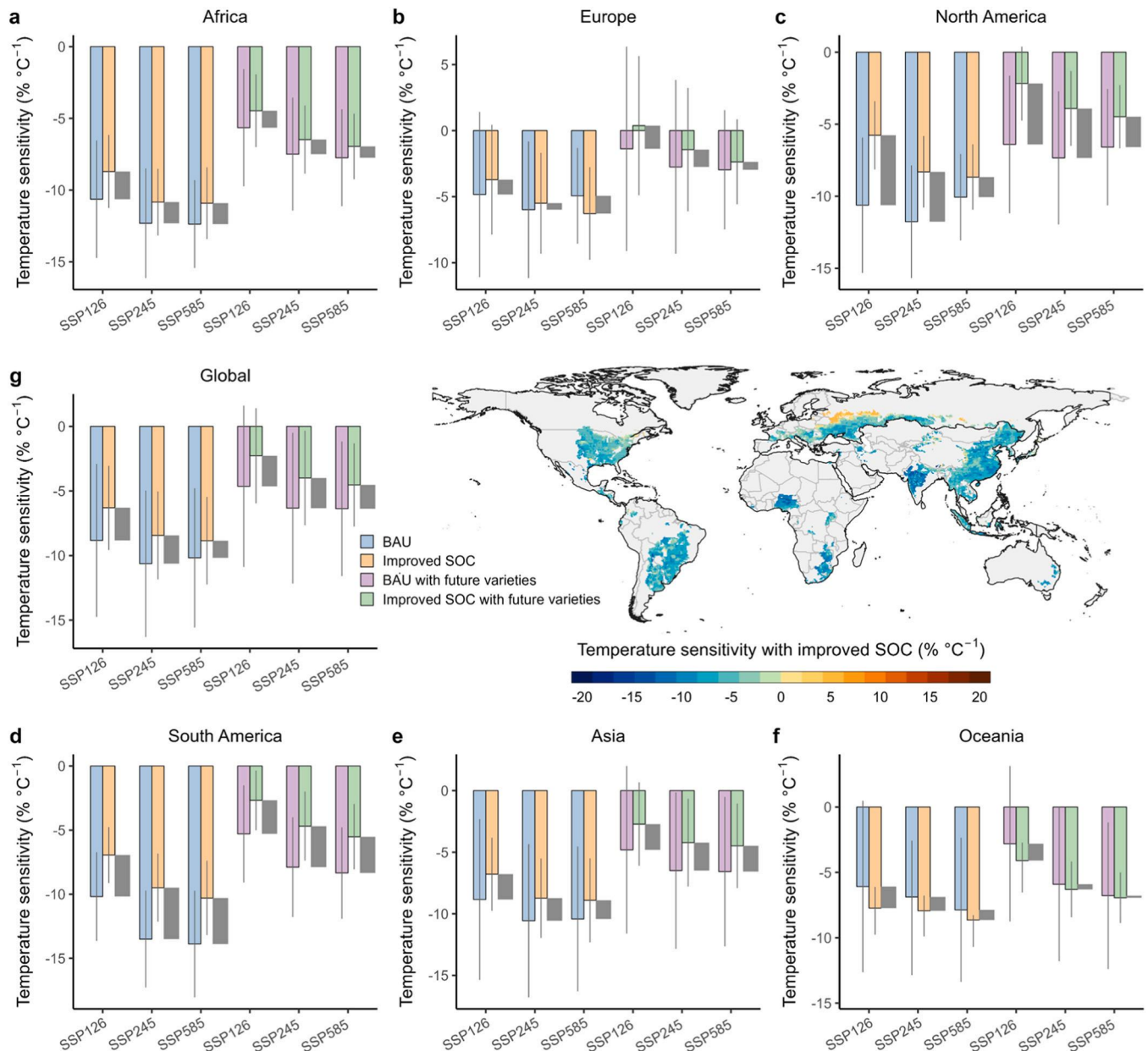
more favorable subsurface water supply and supported greater vegetation biomass compared to clay-rich soils in arid and semi-arid regions. Similarly, our findings suggested that soils with approximately 25 % sand and low clay content, which often classified as medium-textured soils, exhibited lower yield sensitivity to increased temperature (Fig. S3 b-c, g-h). Moreover, the positive effects of SOC improvement on crop yields may be more pronounced in sandy soils than clay soils (Hijbeek et al., 2017; Moinet et al., 2023), indicating a complex interplay among soil properties in modulating crop responses to climate warming.

#### 4.3. Uncertainties and limitations

A primary source of uncertainty in projecting climate impacts on global crop yields stems from differences in the structures, assumptions,

and methodologies of the GCMs used in the ensemble modeling (Asseng et al., 2013; Li et al., 2023a; Rosenzweig et al., 2013; Xiong et al., 2020). Variations in the GCMs and SSPs also contribute significantly to the overall uncertainty (Fig. S1) (Moss et al., 2010). While simulations consistently show a strong negative impact of warming on crop yields in tropical and subtropical regions, uncertainty is notably higher for mid- to high-latitude regions, as reported by Xiong et al. (2020). Despite efforts to reduce these uncertainties, such as parameter optimization (Wallach et al., 2021), ensemble member selection (Li et al., 2023a) and model structure improvement, challenges remain in enhancing model accuracy. Addressing these uncertainties will require more detailed empirical data from field experiments in future studies (Wang et al., 2020).

Furthermore, while some high-latitude regions are projected to become more climatically suitable for crop production under warming



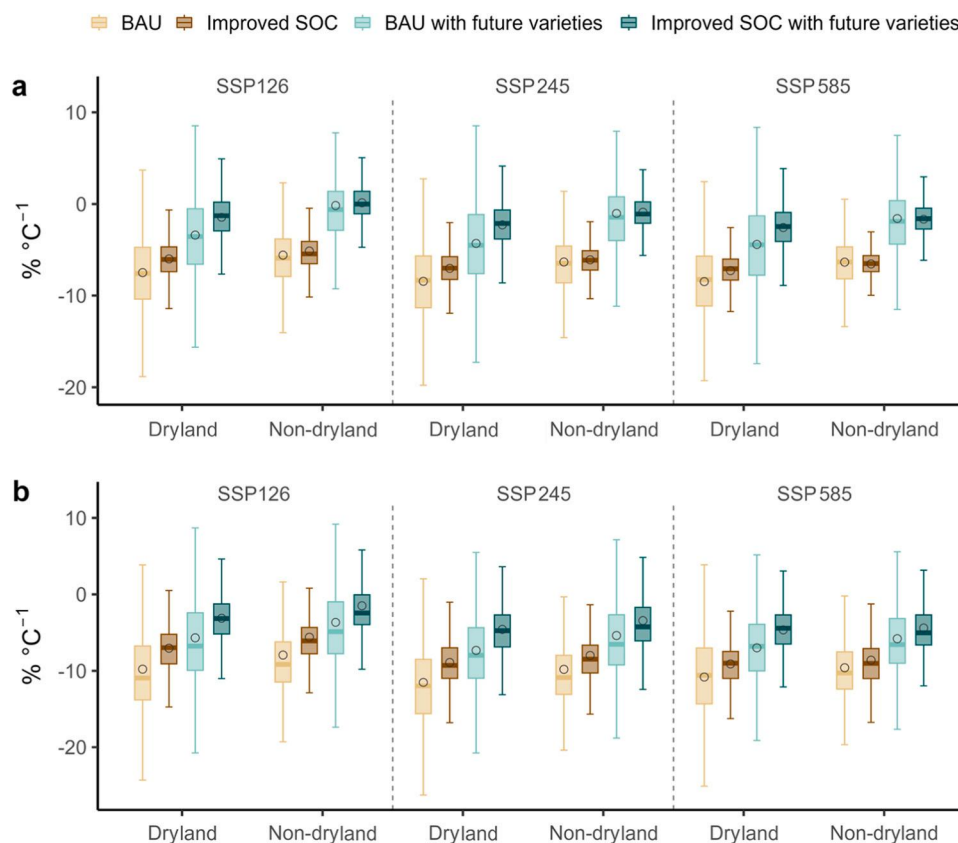
**Fig. 5.** Improved SOC-induced temperature sensitivity changes for soybean. The central map shows temperature sensitivity with improved SOC during 2050–2080 under SSP126. Each bar chart shows the mean values of temperature sensitivity under different scenarios globally and across six continents: Africa (a), Europe (b), North America (c), South America (d), Asia (e), and Oceania (f) and globally (g). Error bars indicate standard deviations, and gray bars show the changes induced by improved SOC under each scenario. BAU means scenario with no SOC improvement.

scenarios, further research is needed to evaluate whether soil quality in these areas will be adequate to support sustained agricultural productivity. Soils, particularly SOC, play a critical role in sustaining agricultural systems, as they are fundamental to maintaining soil fertility and supporting crop production in the context of a changing climate. However, this study may have underestimated the contribution of SOC improvement to crop yield temperature sensitivity due to the unaccounted interconnections among various soil properties. The dataset used here (Zomer et al., 2017) reflects SOC improvements achieved through enhanced farming and soil conservation practices, but the concurrent changes in other soil properties were not included in projections due to data limitations.

#### 4.4. Policy and practical implications

The findings of this study reveal practical soil-based pathways for farmers to combat climate change, and present important implications for sustainable agricultural production. First, the critical role of SOC in mitigating the adverse effects of warming on crop yields highlights the need for policies prioritizing soil health and conservation. Governments and agricultural institutions should encourage the adoption of soil management practices that enhance SOC, such as conservation tillage, cover cropping, residue retention, and crop rotation (Bai et al., 2019; He et al., 2023; Huang et al., 2020; Yang et al., 2024). These practices not only improve nutrient availability and water retention to benefit SOC sequestration, but also strengthen crop resilience to adverse weather conditions. Second, our study underscores the potential of crop varietal development as an adaptive strategy to address climate challenges.





**Fig. 6.** Temperature sensitivity changes induced by improved SOC in dryland (aridity index  $\leq 0.65$ ) and non-dryland (aridity index  $> 0.65$ ) regions for maize (a) and soybean (b) during 2050–2080. Box plots show the 25th and 75th percentiles across 37 general circulation models (GCMs), with whiskers representing the 10th and 90th percentiles. The line and circle within each box indicate the multi-model median and mean values, respectively.

Breeding programs focused on improved heat tolerance, drought resistance, and traits that enhance soil quality, such as deeper root biomass (Cotrufo et al., 2024), could help mitigate yield losses in vulnerable regions. Finally, the observed spatial variation in crop yield responses to warming emphasizes the need for region-specific adaptation strategies. To ensure food security under climate change, integrated measures that combine enhanced soil management, advanced crop varieties, and tailored regional interventions will be essential (Bilotta et al., 2023). Effective implementation of these strategies will require coordinated efforts among governments, researchers, agricultural practitioners, and stakeholders to build resilient and sustainable farming systems.

## 5. Conclusions

This study investigated the effects of soil properties on crop yield responses to increased growing season temperatures across global croplands, and quantified their contributions using statistical analysis and random forest modeling. During the historical period (1980–2010), each  $1^{\circ}\text{C}$  increase in temperature resulted in yield changes of  $-2.3\%$  for maize and  $+3.0\%$  for soybean. However, under future warming scenarios (2050–2080), maize and soybean yields were projected to decline significantly, with losses ranging from  $-6.6\%$  to  $-7.5\%$  for maize and  $-8.9\%$  to  $-10.7\%$  for soybean per  $1^{\circ}\text{C}$  of warming, across the three SSP scenarios. The spatial variability in yield sensitivity to temperature was influenced by soil properties, which explained 51 % of the variation in maize and 59 % in soybean. Among these properties, SOC emerged as the most influential factor, exhibiting a positive relationship with yield temperature sensitivity before reaching optimal thresholds (around  $11\text{--}15\text{ kg C m}^{-2}$ ). Given that current SOC levels are far below this optimal level, SOC improvements through farming and soil conservation practices are projected to mitigate yield losses under future climate

scenarios. SOC improvement could help reduce widespread yield declines induced by warming, particularly in dryland areas. Integrating SOC improvements with the adoption of future crop varieties could further alleviate these yield losses under warming climate. This study highlights the potential of soil-based pathways to enhance the resilience of global crop production to climate change impacts.

## CRediT authorship contribution statement

**Ke Liu:** Writing – review & editing, Resources. **Shengwei Zhang:** Writing – review & editing, Funding acquisition. **De Li Liu:** Writing – review & editing, Formal analysis. **Zikui Wang:** Writing – review & editing. **Matthew Tom Harrison:** Writing – review & editing. **Sien Li:** Writing – review & editing. **Qiang Yu:** Writing – review & editing. **Qinsi He:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Kadambot H.M. Siddique:** Writing – review & editing. **Linchao Li:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Yu Shi:** Writing – review & editing, Methodology. **Puyu Feng:** Writing – review & editing, Methodology.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.eja.2025.127739](https://doi.org/10.1016/j.eja.2025.127739).

## Data availability

Data will be made available on request.

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